MEASUREMENT AND EVALUATION OF MANAGERIAL EFFICIENCY IN ENGLISH LEAGUE FOOTBALL: A STOCHASTIC FRONTIER ANALYSIS

being a thesis submitted for the Degree of Doctor of Philosophy in the University of Hull

by

Peter Michael Dawson

B.Sc. (Bradford)

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The secret of being a good manager is to keep the five players who hate you from the half-dozen who are undecided.

Jock Stein (King and Kelly, 1997)

Coaching is for kids. If a player can't trap a ball and pass it by the time he's in the team, he shouldn't be there in the first place. At Derby, I told Roy McFarland to go and get his bloody hair cut; that's coaching at top level.

Brian Clough (King and Kelly, 1997)

No coach can guarantee results, you can only guarantee a way of playing. Results are in the hands of fate. It is ridiculous to pin the etiquette of success or failure on a coach just because a coin comes up heads or tails.

Jorge Valdano (King and Kelly, 1997)

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INTRODUCTION

The manager is central to the production process within corporate organisations. He or she is responsible for organising as efficiently as possible the transformation of factor inputs into productive outputs. Part of this process requires the manager to monitor and assess the inputs and (in the case of labour) motivate as well. A successful manager will enable a firm to maximise output for a given set of inputs. It is therefore vital that the owners of organisations are aware of the factors that determine managerial performance when choosing a manager.

In recent years economists have shown considerable interest in the performance of the manager in corporate organisations. Although there has been extensive research into the contractual nature of managerial employment, little is known about the precise effect on output of variations in managerial ability and managerial effort. One reason for this is that there may be many managers employed by a firm thus making it difficult to determine which manager is playing the key role. In such circumstances deciphering individual contribution can be problematic. Further, even if the manager can be unambiguously identified there may be difficulties in measuring the other inputs in the production process.

The broad aim of this thesis is to quantify the impact of the manager on firm performance. More specifically, the aim is to measure managerial (technical) efficiency using stochastic frontier analysis and 'explain' variations in technical efficiency across managers in terms of manager human capital and incentives. We use data from English professional football. The football industry provides a unique opportunity for a production frontier study because, in contrast with the corporate sector, the inputs (players and manager) can be unambiguously identified while the output (match results) is transparent. Further, data is readily available on the inputs and the output and there is also a large amount of available data on the firm itself - the football club. As football clubs become more profit oriented it is vital that the clubs' decision-makers (chairpersons, directors and, increasingly, shareholders) make accurate and informed choices as to who to appoint as manager and the kind of incentives to devise when the manager has been appointed.

It is argued that there are two main aspects to managerial performance. Firstly, the ability of the football manager is determined by his[1] human capital (his innate ability plus the ability he acquires through his labour market experience – both as a player and manager). The role of human capital in determining performance remains a live area of debate in the economics literature. Secondly, a manager's performance is related to motivation. If a manager is not properly motivated he is unlikely to exert maximum effort. Effort is intertwined with incentives and we know relatively little about how firm-specific factors affect managerial incentives. Much of the previous literature focuses heavily on the way incentives are built into the design of contracts, but it says little on how incentives actually work in practice. Although work linking managerial performance to manager human capital has been carried out using data on American sports (primarily baseball), there has been no previous work which directly links managerial performance to the characteristics of individual managers for any industry, sport or otherwise, in the UK. Moreover, there has been no previous work, either in the UK or America, which has adequately dealt with both human capital and incentive factors as performance determinants at the level of the manager.

The availability of data in the football industry means we are able, for the first time, to integrate both incentives and manager human capital factors into a model of managerial performance. Although certain characteristics of the football industry make generalisations to the corporate sector difficult (e.g., greater monitoring of managers and the less secure nature of the job), football managers need many of the skills - resource allocation, monitoring, strategic and decision-making - that are required of their industrial counterparts. To this extent, therefore, the skills that determine managerial performance are universal.

The empirical analysis is carried out in two stages. The first stage involves estimating managerial efficiency using a stochastic production frontier. During this stage some experimentation will be necessary to determine the preferred specification of the production frontier. For example, we will consider how the player inputs should be measured, what output measure should be used and what estimation procedure should be undertaken. We do this because the efficiency scores are estimated as deviations from the production frontier and we need to be sure that the specification chosen and the estimation procedure undertaken are appropriate. The main novelty of our approach is to compare efficiency scores using alternative input and output measures. Previous studies (sport in particular) have generally neglected this important consideration.

Having decided upon the appropriate model specification and estimation procedure, the second stage of the analysis seeks to explain the variations in the

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[1] The gender bias is deliberate because football management is 100 per cent male dominated.

managerial efficiency scores in terms of manager human capital and incentives. For the former we investigate whether there is a relationship between managerial efficiency and the manager's record as a player. For example, do players with international experience make better managers? Also, we consider the extent to which managerial experience relates to efficiency. Do managers follow a learning curve? If so, is it specific to the length of time spent with one club or to football management in general? Regarding incentive effects we examine whether managers at bigger clubs and clubs with a relatively high wage bill perform better or worse than managers who operate at smaller clubs with lower wage bills. Also, we wish to determine whether the threat of dismissal acts as an incentive to perform efficiently.

A further benefit of deriving efficiency scores is that they can be used to provide information as to worth of the manager. This is important because even if human capital and incentive factors influence managerial efficiency, the choice of manager is only really relevant if managers make a significant contribution to output. With this in mind, we present some preliminary results on the contribution the manager can make to team output. Of particular concern is the effect of a change of manager on the club's performance.

The thesis is organised as follows. In Chapters 1 and 2 we present a review of the existing literature. Chapter 1 analyses the role of incentives and human capital attributes as mechanisms for determining performance. Much of the previous literature analyses manager performance using wage equations. What is unique in our approach is that we are able to generate a direct measure of managerial performance. The background to the methodology used is provided in Chapter 2. Here we explore the growing literature on production frontier analysis. We are particularly interested in the available estimation procedures and how previous sports studies have utilised this framework in estimating efficiency. A discussion of the football industry is the focus of Chapter 3, while in Chapter 4 we develop the theoretical model of manager performance. Data and methodological issues are addressed in Chapter 5. Chapters 6 and 7 contain the empirical results. In Chapter 6 we generate managerial efficiency scores and consider how alternative input and output measures and alternative estimation procedures affect these scores. Using the preferred model from Chapter 6, Chapter 7 provides a detailed account of how human capital factors and incentives shape efficiency and some preliminary results as to whether the manager actually matters. Finally, Chapter 8 provides some conclusions and recommendations in the light of the empirical results.

CHAPTER 1

MANAGERIAL PERFORMANCE: INCENTIVES AND HUMAN CAPITAL

1.1 Introduction

A major concern of owners of modern corporations is the performance of the manager. One hypothesis says that in the absence of monitoring and incentives, the manager will pursue other, utility-enhancing, objectives that are inconsistent with those of the owners. Alternatively, the manager may just shirk (exert less than full effort). In either case the firm will under-perform (e.g., it will not maximise profits). This is known as a hidden action problem, and reflects the owner (or owners) inability to observe the manager's actions. As a result, the owners have to either directly monitor or devise incentives to "discipline" the manager into seeking common objectives or exert full effort. Following some discussions on the nature and role of management, the first half of this chapter outlines the hidden action framework using a simple static model. Next, the empirical literature is analysed from two perspectives. Firstly, to assess whether managerial contracts contain elements of incentive mechanisms and the type of mechanisms which have been put in place. Secondly, to address the question of whether incentives matter. As will become apparent later on, it is whether the mechanisms have any effect on performance that is important here rather than their role as contractual devices.

In the above scenario, the assumption is that both the owner and the manager have the same information prior to the relationship being established. However, the interests of the owner and the manager might diverge for another reason: the manager might not be as productive as expected given his characteristics. This is known as the hidden information problem and occurs when full information about the manager's characteristics are not known or the manager sends a misleading signal (i.e., his/her expected ability is greater than his/her actual ability).

Here the link between human capital and productivity becomes important. One view - the human capital interpretation - states that human capital factors influence productivity that in turn influences the wage paid. Another - the signalling interpretation - states that human capital factors may indeed influence the wage paid, but they have little or no effect on productivity. In terms of policy decisions, owners would like to know what managerial characteristics improve performance and what characteristics add little to performance. In the second half of this chapter we review the human capital versus the signalling view of productivity.

The hidden action and hidden information problems together constitute the principal-agent problem. Consequently, the firm's owners face two problems: (i) which manager or managers to employ, and (ii) creating the necessary incentives to motivate the manager or managers once hired. Usually, the two problems are looked upon in isolation. Another drawback of previous empirical analysis is that most studies have been concerned with contract design. In order to be able to ascertain whether incentive mechanisms work (managers respond to incentives), and whether human capital accumulation enhances performance, individual-specific measures of performance are required. In the final section of this chapter we focus on the few studies which have attempted to construct individual performance evaluators using subjective and objective criteria.

1.2 The Purpose and Role of the Manager

There is a long tradition in economics of recognising the importance of the manager. Adam Smith (1776) and John Stuart Mill (1848) identify the manager as being employed by an entrepreneur (owner) to oversee the day-to-day operations of the business. Alfred Marshall (1890) was much more explicit. He suggested that management, as the agent who organises production, should be recognised as a separate factor of production.

One consequence of employing a manager is that in doing so the owners are devolving not only responsibility but also control of the firm. The problems that could arise from the separation of ownership from control was first established by Adam Smith (1776):

> The directors of such companies, however, being the managers rather of other people's money than of their own, it cannot well be expected, that they should watch over it with the same anxious vigilance with which the partners in a private copartnery frequently watch over their own (Book V, Chapter 1).

It was, however, not until the publication of *The Modern Corporation and Private Property* by Berle and Means (1932) that the approach was sufficiently articulated towards the characteristics of modern corporations. Berle and Means suggested that where large corporations are owned by a large number of small stock shareholders it is difficult for any one shareholder to control the actions of the managers. Their study created a platform for the development of alternative maximising theories which rejected the simple classical notion of profit maximisation in favour of sales maximisation (Baumol, 1959), growth maximisation (Marris, 1964), utility maximisation (Williamson, 1964), satisficing behaviour (Cyert and March, 1963) and so on.

Although the development of non-profit behaviour led to a major shift of emphasis from the standard profit-maximising assumption, there was little mention of the way relationships, particularly between owners and managers, took place within firms and organisations. New Institutional Economics has developed over the past 25 years or so to specifically look at the relationships that take place within firms and, in particular, forms of contracting for managers and other employees. Agency theory is perhaps the most well known theory in this area, and is discussed at length in Section 1.3.

Given the above, one is entitled to ask why are managers employed at all? A manager is usually employed because of the gains to specialisation that occur when the owner employs a manager with specialised skills and traits, creating a "potential" comparative advantage in production[1]. The role of the manager is crucial in the production process: he/she has to organise production as efficiently as possible given the resources (land, labour, capital) available in any given time-period. Managers are unique in the sense that they are required to co-ordinate and monitor the work of other labour and non-labour inputs. In effect, managerial effectiveness can be partially described by

[1] Firm performance should be greater when a manager is employed compared to the performance that would occur if the owner directed operations. It is termed "potential" because, as we have already eluded to, and as we will see in Sections 1.3 and 1.7, these gains may not be realised in practice.

the "degree of congruence between actual and expected practices and performances" (Hales, 1986, p. 111).

What then is the nature of the work involved and what skills do managers need to carry out these roles?

Following Mintzberg (1973), managerial activity can be divided into three categories: (i) interpersonal relations, (ii) information processing roles and (iii) decision-making roles. The roles of figurehead, leadership and liaison constitute interpersonal behaviour. Leadership is the most important. It involves guiding and motivating workers through both verbal praise and criticism, and formal promotion and dismissal. The liaison role involves aspects of networking (the ability to trade information with other organisations), whereas the figurehead role identifies the manager as the head of the organisation. The information processing role involves the use of information (reports, meetings) to monitor workers and analyse performance. Some of this information may be passed around the organisation (disseminating role) or communicated to people outside the organisation (spokesperson role). As an entrepreneur, the manager either improves on existing arrangements or changes them to exploit new opportunities. The final category of decision-making involves resource allocation decisions relating to staffing matters, purchasing of equipment and materials, and the choice of service provision. If firm-level crises occur (i.e., unforeseen events such as staff conflicts and industrial accidents), the manager is required to act as a disturbance handler. Finally, as a negotiator the manager is involved in employee contracts, loans, and customer and supplier relations.

The three categories are not mutually exclusive. For example, consider the role of negotiator. If the manager is negotiating a contract with a new supplier, by doing so he/she is acting as a figurehead, a resource allocator and a spokesperson. Also, these roles are offered only as a general guide. The manager's role will not only differ from institution to institution, but also in terms of position in the organisation's hierarchy. The structure of today's standard organisation resembles that of an hourglass (Keuning, 1998). At the top of the glass are the many owners (shareholders) followed by a small number of boardroom directors and then the company manager. Below the company manager come several middle and lower-level managers. And finally below these managers comes the general workforce.

An important consideration in the above is that the role of the middle and lower-level managers will be different to that of the company manager. For example, managers further up the organisation's hierarchy are required to take on more responsibility and are concerned with the long-term objectives of the company. Typically, upper level management are concerned with planning decisions in excess of five years, decision-making and leadership. Middle and lower level management, on the other hand, are more likely to be concerned with monitoring performance and general staffing matters on a day-to-day basis[2].

Regardless of level, all managers require certain skills or traits in order to carry out these functions effectively. Yukl (1994) proposes a three skill taxonomy to managerial effectiveness. Firstly, technical skills involve the necessary knowledge to carry out a particular activity, including detailed knowledge of processes and products produced both by the firm and its competitors. Secondly, communication skills are demonstrated by the manager's knowledge of human behaviour. The better managers are the ones that are not only able to communicate clearly, but also understand and co-operate with the workforce using interpersonal skills such as tact, charm and diplomacy. These skills are especially important in motivating the workforce. Finally, conceptual skills such as analytical ability, judgement, foresight, intuition and certainty are important for effective planning and organising. For example, the manager will have to make strategic decisions based on how the external market influences company performance. The ability to do this is determined by both analysing events that have taken place and anticipating problems and changes that may occur[3].

Each of these skills either come naturally to the manager (i.e., he/she "is a born leader"), or are acquired through schooling (formal education) and labour market training or experience. Critically, the manager is evaluated in terms of achieving the firm's objectives through organising, co-operating and motivating the workforce. In the football industry the skill with which these activities are implemented are vital because they affect not only the individual player but also the performance of the team. See Chapter 3 for details.

1.3 Theory of Agents

Agency theory is concerned with the relationships that exist between a principal and an agent. In the context here, the principal is the owner and the agent is the manager[4]. As mentioned in Section 1.1, a conflict exists because the goals of the manager may not

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[2] As we will see in Chapter 3, these are the main roles of the football manager.
[3] How these functions and skills apply to football managers will be discussed in Chapter 3.

match the goals of the owner. Such goal divergence arises in many other areas of economics too (e.g., sharecropping, insurance, education and law enforcement). In fact, "The agency relationship is a pervasive fact of economic life" (Arrow, 1985, p. 37).

Basically goal divergence occurs because of asymmetric information: one party (the agent) has more information than is available to the other (the principal). Consider the sharecropping relationship. The principal (landlord) hires an agent (the sharecropper) but does not know how much effort the sharecropper exerts to produce the crop. Clearly the agent has more "information" about his performance than does the landlord, thereby creating information differences between the two parties.

In a firm setting the owner hires the manager to oversee the operations of the firm due to the abilities and specialised knowledge outlined in Section 1.2. Usually this creates a divorce of ownership between the two parties[5]. As Berle and Means (1932) succinctly put it:

> The separation of ownership from control produces a condition where the interests of the owner and of ultimate manager may, and often do, diverge, and where many of the checks which formerly operated to limit the use of power disappear (p. 6)[6].

The question is, therefore, how can such goal divergences be realigned? This leads us to the hidden action model.

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[4] Equally, agency relationships exist between management and the workforce and between the firm and its customers.
[5] Unless the owner is also the manager.
[6] Two other points they make are worthy of mention. Firstly, there is widespread shareownership such that no one individual has a significant holding of shares in one company. Secondly, the shareholdings of the manager is relatively small. We shall return to these points in the empirical investigations of Section 1.4.

1.3.1 The Hidden Action Model

The hidden action model, more commonly known as principal–agent (P-A) analysis[7], was formalised in the 1970s. The theory seeks to explain how incentives are used to align the manager's interest with that of the owner given that there is imperfect information regarding the manager's effort (action)[8]. It also considers the nature of the manager's contract under various risk preferences of the two parties. The main tenet of the theory is the trade-off that exists between providing incentives and insuring against risk.

To simplify matters the basic theory outlined here deals with one owner and one manager in a static, one-period framework. The two parties each have definable utility functions: the owner derives utility from wealth (firm profits) alone; the manager derives utility from wealth and disutility from effort. For simplicity, the manager's utility function is separable[9]. Given that the owner pays the manager to act on his/her behalf, the net wealth of the owner will be wealth minus the fee paid to the manager. In addition, both parties are assumed to act in their own self-interest and seek to maximise expected utility.

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[7] This section follows the early work in the literature of Ross (1973) and Mirrlees (1976). A similar approach, "positive" agency theory (Jensen and Meckling, 1976; Fama, 1980) deals with the same problem, providing similar outcomes, but without the analytical rigour of the mathematical P-A models. The P-A approach is preferred because it provides the basis of the theoretical model developed in Chapter 4. Prendergast (1999) offers a recent review. Two other theories have developed within the New Institutional Economics area: transaction cost theory (Williamson, 1985) and the theory of property rights (Alchian and Demsetz, 1972). In contrast to agency models which are concerned with the nature of contracts and individual behaviour within firms, these two approaches place more emphasis on the nature of the firm as a 'nexus of contracts' and as a more efficient alternative to market-based transactions. There are notable similarities between the approaches but they are beyond the scope of this study.

[8] There is a debate in the literature as to what effort means. Some argue that it refers to physical and mental exertion, others suggest that it is the extent to which managers can undertake other (non-profit) utility maximising objectives. Here, the two aspects are used interchangeably.

[9] This means that changes in monetary remuneration do not induce changes in the disutility from effort, and is analogous to assuming that there are no income effects.

The owner observes the outcome but not the effort, and a state of nature term is introduced to randomise the outcome. Without a state of nature term the owner could stipulate a desired outcome, only rewarding the manager when this desired outcome has been achieved. The random term is designed so that a higher level of effort by the manager will always result in a more favourable outcome for the owner[10]. Both parties hold the same beliefs about the state of nature term[11].

Given the above, the owner's utility function is:

$$U_O = U_O\,(Y - S(w)) \tag{1.1}$$

The manager's utility function is:

$$U_M = U_M\,(S(w)) - \phi(e) \tag{1.2}$$

U_O and U_M refer to the utility functions of the owner and manager, respectively[12]; Y is the output of the firm and is functionally related to the effort of the manager and the state of nature term (θ) as described above[13]; S is the utility of monetary remuneration (wage) w; e represents the effort level of the manager; and ϕ represents the monetary valuation of the disutility of effort.

[10] Known as the likelihood proposition.
[11] This is a highly restrictive assumption given that asymmetric information exists (i.e., how reasonable is it to assume that both the owner and the manager posses the same information about the state of the environment?). To date, the literature has been silent on this matter.
[12] For the owner: $U_O' > 0; U_O'' \leq 0$. For the manager: $S' > 0; S'' \leq 0; \phi' > 0; \phi'' > 0$.
[13] Another important assumption is that the manager chooses effort before the state of nature is known. Also, effort increases at a diminishing rate ($e' \geq 0, e'' \leq 0$) and the state of nature term is a positive function ($\theta' > 0$).

Given that the owner's objective is to maximise profits and the manager's objective is to maximise remuneration and minimise effort, then to arrive at the Pareto-optimal contract we need to maximise the utility of the owner given the utility level of the manager. In addition, the manager's utility must satisfy what is called the individual rationality or participation constraint. This is the market derived rate of reservation (either the opportunity cost of employment in a similar establishment or the opportunity cost of leisure)[14]. Namely:

$$U_M(S(w)) - \phi(e) \geq W_{Min} \tag{1.3}$$

where W_{Min} is the reservation wage. If this constraint were not binding then the manager would not participate in the contract. We are now in a position to analyse contractual designs under different risk preferences and information (monitoring) levels.

Owner Observes the Outcome Only

To begin we assume that the owner is risk-neutral ($U_O'' = 0$), the manager is risk-averse ($S'' < 0$) and the owner only observes the outcome (Y)[15]. To ease exposition, effort is a discrete choice variable: either high effort (e_H) or low effort (e_L) can be chosen. However, because effort only influences the probability of occurrence of various outputs we let p_H be the probability that output Y is observed if the manager chooses effort e_H, and p_L is the probability that Y is observed if the manager chooses effort e_L. In order to induce the manager to put in high effort the wage obtained for high effort should be

[14] This is another aspect of the literature that is always assumed yet seldom explained. Smith and Szymanski (1996) offer an explanation of the empirical importance of this constraint.

greater than the wage obtained under low effort. This is known as the incentive compatibility constraint and is expressed as:

$$U_M(S(w))p_H - \phi(e_H) \geq U_M(S(w))p_L - \phi(e_L) \tag{1.4}$$

The optimal incentive scheme is a constrained maximisation problem solved using either linear programming techniques (maximising equation (1.1) subject to equations (1.3) and (1.4)), or via the Lagrangian method as follows:

$$L = (Y-S(w))p_H - \lambda[\ \phi(e_H) + W_{Min} - U_M(S(w))p_H]$$
$$- \mu\, [\phi(e_H) - \phi(e_L) - U_M(S(w))\ (p_H - p_L)] \tag{1.5}$$

where λ is the Lagrangian multiplier of opportunity cost constraint[16] and μ is the Lagrangian multiplier of incentive compatibility constraint. Differentiating L with respect to $S(w)$[17], yields:

$$-p_H + \lambda U_M^{\prime}(S(w))\, p_H + \mu U_M^{\prime}\ (S(w))\ [p_H - p_L] = 0$$

or

$$\frac{1}{U_M(S(w))} = \lambda + \mu\left[\frac{1-p_L}{p_H}\right] \tag{1.6}$$

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[15] In fact, the owner will observe the profit. However, the fee is a function of the outcome alone.
[16] Assuming the opportunity cost constraint is based on high effort.

Equation (1.6) determines the form of the incentive scheme. Given the present arrangement of a risk-averse manager, the solution to the problem is to make the wage contingent on the owner's return ($\mu > 0$). The wage level is determined by p_L/p_H, it measures the likelihood of observing low output, and hence low expected profits (π_L), given that the manager chose e_L as a ratio of observing high output, and hence high expected profits (π_H), given that the manager chose e_H.

The solution is sub-optimal. The manager has to bear some of the risk in order for the owner to motivate effort. The optimal arrangement for the manager, given risk aversion, is full insurance (constant wage), but this arrangement is sub-optimal for the owner as effort will be minimised since the likelihood function suggests that the low output outcome will occur. This is the basis of the trade-off that exists[18].

Both Owner and Manager are Risk-Neutral

Now consider the case where both the owner and manager are risk-neutral ($U_O'' = 0, S'' = 0$, respectively). Unlike the previous example, where the outcome was sub-optimal, under conditions of manager risk-neutrality a Pareto-optimal solution exists

[17] Kuhn-Tucker first-order conditions.

[18] Grossman and Hart (1983) argue that the above formulation is unsatisfactory because second-order conditions are ignored. The manager's problem is to maximise expected utility subject to a given incentive scheme. If multiple effort levels exist (i.e., indifference curve is characterised by several points of inflexion and turning points) then the point of optimum for the owner (highest indifference curve which satisfies equation (1.6)) may not coincide with the global maximum for the manager. Indeed, Grossman and Hart demonstrate that the global maximum for the manager does not satisfy equation (1.6). Only if there is a unique solution will the two points be congruent. For our purposes we assume a unique optimum does exist.

even if the owner cannot observe the manager's effort[19]. Combining equation (1.1) with the participation constraint (equation (1.3)) yields:

$$U_O = (Y - S(w)) - \phi(e) - W_{Min} \tag{1.7}$$

As before, the owner wishes to optimise the manager's effort for the lowest possible wage. The optimal contract is achieved if the owner 'sells' the firm to the manager at a price (P) which is equal to optimal effort (e_H):

$$P = (Y - S(w))\pi_H - \phi(e_H) - W_{Min} \tag{1.8}$$

Effectively the manager becomes the residual claimant to the profits of the firm after 'buying' the firm, whereas the owner receives a fixed payment based on the sale of the firm. The manager's wage can therefore be expressed as:

$$W = (Y - S(w))\pi_H - \phi(e) - P \tag{1.9}$$

It is clear from equation (1.9) that it is in the best interests of the manager to appropriate high effort; anything less than high effort will reduce his wage below the reservation wage. However, he now bears all the risk. In the present example this does not matter because the manager is risk neutral. Also, as the incentive compatibility constraint (i.e., equation (1.4)) does not apply the wage paid to the manager will be lower. Essentially, this kind of arrangement removes agency problems because the manager becomes the owner. It is highly unlikely, however, that any manager is risk-neutral.

[19] The results are unchanged if the owner is risk-averse.

In the limiting case of full (costless) information the Pareto-optimal contract is achieved even if the manager is risk-averse. Given risk-aversion, the manager requires full insurance. But since effort is fully observed, the owner can initiate a forcing contract that elicits strong punishment (sacking, demotion, and so on) if the manager does not exert high effort. Using equations (1.1) and (1.3) but not equation (1.4) since again it is not binding[20], the first-best solution implies that the manager obtains a fee for high effort ($S(w) = W_{Min} + \phi(e_H)$) and a suitable punishment ($W_{Min} + \phi(e_L) > S(w)$) for low effort.

A more interesting, and more realistic case, is when information regarding effort is available but it is imperfectly observable. Once more, a net gain occurs so long as the information is costless to obtain. Furthermore, Holmstrom (1979) and Shavell (1979) demonstrate that the information source needs to affect the likelihood ratio in equation (1.6). The numerator and denominator in equation (1.6) are functions of outcome and effort. Introducing an additional information term, say ζ, alters the likelihood ratio and the manager will receive a different remuneration because ζ alters state contingencies (Holmstrom, 1979). Basically, ζ gives more information about the effort than the outcome alone. This is likely to improve the second-best state by reducing the risk that comes with the state of nature term by reducing the likelihood of wrongly penalising high effort and wrongly rewarding low effort[21].

The theoretical model outlined above is somewhat restrictive in that a single owner deals with a single manager in a single time-period. For real-world applications

[20] Since equation (1.4) is not binding, μ=0 and so, using equation (1.6), pay is equal to $1/\lambda$.

there are likely to be many managers working for several owners in a single firm, and these relations occur repeatedly[22]. In multiple agent models the uncertainty of outcome can be overcome by comparing the performance of identical managers, facing a common state of nature, based on average performance. Holmstrom (1982) demonstrates that the mean output of all the agents acts as a sufficient statistic (i.e., affects the likelihood ratio) for information regarding the state of nature term[23, 24]. For a multi-period setting, the Pareto-optimal outcome can be achieved by basing remuneration on average performance of the agent(s) over time, providing the relation between action and performance is the same in each period. As the number of repeated relations approaches infinity the randomness is removed and the first-best solution once again occurs (Radner, 1981).

The problem of agency arises because effort cannot be fully observed. Even though an optimal solution may exist if the manager is risk neutral, common sense suggests that most managers are not risk-neutral - the majority of managers would prefer a greater proportion of their remuneration to be fixed. The mechanisms of monitoring and incentive systems originate as efficient responses to the co-operation problem. Compared to other industries the problem of agency is likely to be less severe in the football industry because monitoring is much more transparent and there is a high rate of

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[21] In equation form: $Y = e + \theta / \zeta$.

[22] The single owner - single manager relationship is, however, not uncommon for the majority of football clubs.

[23] Unlike the single agent setting, even if there is no state of nature term moral hazard can occur due to free-riding. This time group incentives (i.e., collective punishment strategies) are required to eliminate the individual incentive to cheat when only joint production is observed.

[24] The multiple agents model has been applied to American Football (Atkinson *et al.*, 1988). The P-A relationship is formulated in terms of individual club owners (the agents) and the league's governing body (the principal). The governing body wishes to maximise the revenue to the league as a whole (social profits), whereas the club owners wish to maximise individual (private) profits. It is assumed that the governing body cannot impose the distribution of the playing inputs and does not have information as to how individual players affect the performance of different clubs. Atkinson *et al.* argue that revenue sharing of broadcasting fees and gate receipts encourages the optimal (i.e., league revenue maximising) distribution of playing talent across teams.

managerial turnover. Nevertheless, as we will argue in Chapter 4, effort levels may very *within* the football industry because clubs differ in size and have different policies on payment and turnover.

1.4 Testing the Relationship Between Incentives and Effort

In this section we review the many mechanisms that can be used to align the manager's interest (or induce higher effort) with those of the firm's owners. In accordance with the theoretical model outlined above, the owners can offer incentives within the wage paid or induce incentives directly by monitoring the manager. If the theory is correct, then the manager's contract should exhibit the use of incentives.

Implicit within the theoretical framework is the view that incentives matter. That is, if incentives are introduced then managerial performance will increase (managerial misbehaviour will fall). This is a more difficult question to address, and, hence, has only just begun to be analysed. We briefly review the evidence presented to date in Section 1.6.

1.4.1 Pay-Performance

Without doubt the most common approach has been to test the relationship between the manager's pay and firm performance. Estimation follows a least-squares linear or logarithmic approximation[25]:

[25] Holmstrom (1979) was the first to suggest this by suppressing the state of nature term, using statistical distributions instead. Namely:
$Y = e + \theta$
where $\theta \sim N(0, \sigma^2)$.

$$w_i = b_0 + b_1 Y_i \quad (1.10)$$

where w_i is total managerial pay and Y_i is the firm's performance. Equation (1.10) is a reduced form of the P-A model analysed in Section 1.3.1. The specification seeks to measure the extent to which pay-performance incentives are used. The constant term (b_0) can be classified as the base pay, or insurance wage, component that contains unobserved (possibly time-invariant) effects. The slope term (b_1) measures the extent to which managerial pay[26] is determined by performance. If $b_0 = 0$ (i.e., the constant term is statistically insignificant), the manager's pay is made up of incentives only (i.e., no insurance pay is given). Whereas, if $b_1 = 0$ (i.e., the slope term is statistically insignificant) the manager is offered full insurance but no incentives[27]. Two questions need to be addressed: how is firm performance to be measured and how should pay be defined?

Firm Performance Measures

There have been many debates in the literature as to which measure of firm performance is the most closely related to managerial pay. Early work following the specification of equation (1.10), using either cross-sectional or pooled data[28] (e.g., Roberts, 1959) found that the remuneration of managers in the American manufacturing sector was determined more by company size - measured as the logarithm of net assets - than by company profitability. Cosh (1975) and Meeks and Whittington (1975) recorded similar findings

[26] In the following discussions pay, wages and remuneration are used interchangeably.
[27] These outcomes are similar to those described in the earlier theoretical section.
[28] In fact these early studies did not specifically estimate equation (1.10), instead they were more concerned with the objectives of the firm (i.e., empirical tests of managerial and behavioural models) rather than contract design per se. Nevertheless, there is a strong link between the two approaches.

for UK companies. In contrast, both Lewellen and Huntsman (1970) and Masson (1971) argue that company profits are the main motivating force in managerial remuneration[29].

Apart from the differences in data sources and model formulation, Ciscel and Carroll (1980) criticised the conclusions offered by these early studies because of their neglect of possible econometric considerations. In their view inconsistencies arose because none of the aforementioned studies had adequately account for multicollinearity, heteroskedasticity or simultaneous equation bias. Specifically, they argue that using both a measure of profit and a measure of sales (as recorded in company accounts) in a pay-performance equation, as many of the above studies had done, is likely to result in two econometric problems. Firstly, sales and profits are highly correlated - higher sales results in higher profits - so that when entered together one or both of the measures may well be insignificant. Also, the functional relationship between sales and profits means that profits will be correlated with the error term. One solution to both of these problems is to regress remuneration against sales and residual profit (i.e., profit not determined by sales), or remuneration against profits and residual sales.

Having accounted for these potential econometric problems, Ciscel and Carroll conclude that:

> Executives are paid for increasing profits, whether through sales growth or cost control...since the sales variable may also serve as a measure for firm size...there is a strong indication that decisions concerning executives' salaries are influenced by several aspects of corporate performance (p. 13).

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[29] The term manager is used generically to cover both the chief executive officer (in American studies), and the highest-paid director (commonly used in UK studies).

A further problem with equation (1.10) is that it measures the absolute level of managerial wage against firm performance. As will be demonstrated later, managerial pay, and managerial performance, depends on the quality and ability of the manager, his/her past performance and his/her position in the firm's hierarchy (i.e., his/her level of responsibilities). Any cross-sectional specification such as equation (1.10) will only accurately reflect the pay-performance relationship if these factors are time-invariant (i.e., form part of the constant term). However, even if they are fixed over time an omitted variable problem exists because these other factors are likely to vary across managers (Murphy, 1985). Murphy addresses the problem by estimating a fixed effects version of the model[30].

An alternative to the fixed effects model, and more common way of dealing with this problem, is to introduce a first-difference operator:

$$w_{it} - w_{it-1} = b_0 + b_1 (Y_{it} - Y_{it-1}) \qquad (1.11)$$

Equation (1.11) regresses the difference between pay in the current time period and pay in the previous time period on the first-difference of company sales or company profits. Unlike the simple cross-sectional approach that looks at the absolute level of remuneration, the first-difference method considers the growth of company sales or profitability on the growth of managerial remuneration.

Apart from econometric considerations, the strength of the relationship between pay and performance in either equation (1.10) or equation (1.11) depends on how

[30] More details about fixed effects models can be found in Chapter 2. The question of managerial ability (quality) as a wage and performance determinant is addressed in Section 1.7.

performance is measured. Many of the above studies use asset value to proxy for sales and accounting rate of return to measure profitability.

The accounting rate of return is usually expressed as accounting profit divided by accounting value of total assets. There are two frequently used measures in the accounting and financial economics literature. Accounting return on assets (ROA) is earnings before interest and taxes divided by book value of assets; return on equity (ROE) expresses the firm's earnings before extraordinary items and discontinued operations as a ratio of average common shareholders' equity. Antle and Smith (1986) find both measures are positive and statistically related to remuneration.

The accounting-based measures may, however, give a spurious relationship between pay and performance. This is because the manager can manipulate the reporting of accounting data. For instance, the manager may be unwilling to invest in projects that have high initial start-up costs or are considered risky ventures which, although may bring long-term benefits, would affect the firm's short-term profitability. A more popular way of empirically measuring firm performance is to use market-based methods such as shareholders' wealth measures. The empirical importance of such measures reflects the ownership structure of today's organisations (i.e., shareholders are the owners).

Conyon and Leech (1994) define shareholder wealth as dividends plus share price in the current period, divided by share price in the last period multiplied by market value of the firm at the start of the current period. Conyon and Gregg (1994) and Gregg *et al.* (1993) offer similar definitions. Each of these three UK studies report relatively low, but statistically significant, pay-performance sensitivity coefficients: $b_1 = 0.027$ (Gregg *et al.*, 1993), $b_1 = 0.020$ (Conyon and Gregg) and $b_1 = 0.059$ (Conyon and Leech). At the median salary rate these latter two values are equivalent to £221 and £375, respectively – hardly indicative of a strong relationship. In fact, research suggests the relationship is declining (Conyon *et al.*, 1995), and may even be negative (Gregg *et al.*). The American literature supports the results found in UK studies[31]. Jensen and Murphy (1990a) estimate the pay-performance coefficient as 0.0000135 (i.e., for every $1,000 increase in shareholder wealth the manager receives about 1.35 cents). This is equivalent to a pay-performance elasticity of approximately 0.1, and is comparable with other American studies by Couglan and Schmidt (1985) and Murphy (1985).

Within these studies sales measures continue to be used because both accounting measures and market-based measures are noisy approximations to managerial performance. Market-based measures are particularly noisy because they include aspects such as governmental decision-making, and international and general domestic conditions, which are not under the control of the manager. The inclusion of a sales measure, whilst reducing the impact of the profitability measure (although in many cases still significant), seems to provide a more sensitive pay-performance measure. Again, the magnitude is not large: 0.07 (compared with a shareholder wealth measure of 0.052) in Conyon and Leech (1994), whilst Jensen and Murphy (1990a) find that the two measures are statistically the same.

[31] See, for example, Jensen and Murphy (1990a; 1990b), Murphy (1985) and Gibbons and Murphy (1990).

All of the studies outlined above use a rather narrow definition of remuneration: the manager's salary plus bonuses. One possible reason for the small magnitude of the pay-performance coefficient may be that this definition of pay is too restrictive. Jensen and Murphy (1990a) present results for a total compensation measure[32]. However, this only marginally improves the sensitivity coefficient (3.3 cents for every $1,000 increase in shareholder wealth)[33].

Alternatively, owners could design pay systems contingent on internal contractual devices. Share or stock options may motivate managers correctly. The idea is as follows. Managers are offered the right to purchase shares in the future[34] at a fixed, significantly discounted, price agreed now. The manager does not have to purchase the shares when the time comes, but if at the future purchase date, share prices are substantially higher than the price at which they were originally offered the manager is likely to make significant gains. Therefore there is an incentive for the manager - partially through higher effort - to create higher future share prices.

Stock options provide incentives in two ways. Firstly as options advanced in the current financial year and, secondly, unexercised options previously awarded. Jensen and Murphy (1990a) estimate changes in the value of stock options and find that, on

[32] This total compensation measure is based on the Forbes definition that includes salary, bonuses, value of restricted stock, savings and thrift plans. Data on managers in UK companies are usually restricted to salary and bonuses only.

[33] There is also a timing issue. Managers may well be paid for past performance. Bonus payments may be paid prior to the publication of detailed financial statements for the current fiscal year. Here the bonus payment follows a lag adjustment - bonuses paid this year are the result of performances the previous year. Jensen and Murphy (1990a) and Conyon and Leech (1994) provide evidence of pay being paid for past performance.

[34] In the UK, options cannot be exercised within three years and cannot be left to mature longer than 10.

average, an increase in shareholder wealth of $1,000 increases the value of chief executive officer stock options by 14.5 cents. Although this value is larger than the one recorded for the profitability measure, it is again small and the R^2 value of 0.08 suggests that stock options only account for a relatively small part of the total remuneration package. An anomaly seems to be provided by Murphy (1985) in that a negative option value is recorded. However, the negative value reflects lower option prices for low-performance periods (i.e., lower option price results in a higher option value). Evidence of stock options in UK companies is provided by Main *et al.* (1996). In contrast to the American literature, their analysis suggests that stock options do play an important role in shaping managerial remuneration. For example, in the managerial earnings equation without stock options the estimated coefficient on firm performance (measured as share performance) is 0.233[35]. Including stock options in the remuneration figure increases the coefficient to 0.898.

A further way remuneration can be used to induce effort is through stock ownership. Cosh and Hughes (1987) compare a sample of the largest American firms from the Fortune list with the same number of large UK companies from the Times 1000. They find that the median percentage of shares held by managers in America and UK is low: the percentage of shares held beneficially is 0.03 (0.06 including stock options) and 0.25 (0.54) for the UK and America respectively. However, in monetary terms, the median market value of holdings (dividend income) for the UK manager is £19,000 (£1,500). In America the holdings are even more substantial: median value of holdings is £1.8 million which corresponds to a dividend yield of £66,000. This is because small share holdings in the largest companies can represent huge additions to

[35] These figures represent the returns to the highest-paid director in order to make comparisons with the UK studies already mentioned.

income and wealth. Given that the analysis was conducted using the financial period 1980/81, the shareholdings of today's managers are likely to be even higher. Indeed, The Sunday Times annual survey of executive pay (1998) reported that the median remuneration paid to managers of UK companies is over one million pounds, of which the value of share incentives (stock options and holdings) is about half a million.

1.4.2 Incentives Through Monitoring

Overall the results of the pay-performance studies are weak. Stock ownership perhaps gives the strongest indication of aligning interests, but this may reflect a personal investment by the manager rather than a contractual device used by owners. However, thus far we have concentrated on the use of incentives via contractual means. This only gives a partial analysis of the way managerial incentives can be introduced. Incentives can also be provided through monitoring.

<u>Indirect Monitoring: Relative Performance Evaluation</u>

The performance measures mentioned above are noisy approximations to firm performance. They include common external shocks to both the firm and the industry. These shocks are usually thought to be beyond the manager's control. The tenet of relative performance evaluation (RPE) is that the specified performance measure should be relative to other managers in the same firm, or other managers in the same industry, net of any common fluctuations (such as stock market movements). The usefulness of RPE is as an additional source of information of the kind proposed in Section 1.3.

Rather than giving information about manager effort, RPE gives information about the common state of nature. Typically, empirical studies measure the relative performance of managers in different firms filtering out the common shock element. Both Gibbons and Murphy (1990) and Conyon and Leech (1994) find evidence, albeit weak, that managerial remuneration is negatively related to industry (value-weighted portfolio based on standard industrial classifications) and market returns (based on stock market data).

Lazear and Rosen (1981) link the relative performance of managers in the same firm to promotional activity. Promotion is viewed as a kind of tournament whereby individuals compete with one another for the higher-rank in the organisation[36]. Using a single-period tournament model, Lazear and Rosen argue that in areas such as academia and building societies, where capturing an appropriate performance measure is more problematic, tournament systems may be beneficial. However, in certain circumstances promotional activity will not be an effective incentive device. Consider a manager who already has a relatively high standing in the company he/she is working in. Promotional incentives here are either weak, or in some cases (such as CEO or highest-paid director), do not exist at all. Alternatively, even when promotion systems operate the probability of promotion may be low. This can occur either because of the number of setbacks the employee has received in the past, or because the employee who occupies the higher

[36] Ehrenberg and Boganno (1990) use tournament theory to test whether incentives create the desired effort in European professional golf. In tournaments, it is the rankings of managers and the prize (promotion) differentials rather than the differentials between managers that are important.

rank is relatively young - long career horizons of superiors may create disincentive effects on those employees immediately below.

Direct Monitoring: Corporate Governance

A more common method of monitoring the manager is through corporate governance. Corporate governance refers to the establishment of boardroom committees. One of their functions is to direct, control and set pay. The role of such committees was brought into prominence in the positive agency literature (Fama, 1980; Fama and Jensen, 1983). The existence of boardroom committees in large UK and America organisations is almost universal. Conyon (1994), using a retrospective postal questionnaire sent to companies on the Times 1000 list, asked about the existence of boardroom committees in both 1988 and 1993. In 1988, close to 60 per cent of the responding firms made use of such committees. By 1993 the figure had risen to 96 per cent.

Williamson (1985) best describes the theoretical appeal of boardroom committees by arguing that in the absence of a committee the manager would "write their own contracts with one hand and sign them with the other" (p. 313). In essence, boardroom committees are meant to operate on behalf of the owners (i.e., shareholders) of the company. Their importance is greater the greater is the dispersion of shareholder wealth, where the individual shareholder cannot appropriate full monitoring of the manager. In effect a free-rider problem exists. If one shareholder acts to monitor the manager the resultant gains (increased firm profitability) will be reaped by all shareholders. Monitoring in this case is a public good.

If boardroom committees are to work then one of the requirements is the control of managers' pay. The available evidence on this is mixed. Main and Johnson (1993) find that unexpectedly boardroom committees increase pay. Conyon (1997) argues that there is a negative relationship between boardroom committees and the growth of managers' pay[37] in firms using committees. The composition of the committee itself may also have an important bearing on the pay of the manager. If the committee is designed so that the same person undertakes the roles of manager and chairperson, then this allows the manager to pursue his/her own objectives rather than those of the shareholders. However, neither Conyon nor Main and Johnson find support for this proposition.

Since monitoring and incentive methods are considered as substitutes, a further test of the significance of committees would be evident in the re-structuring of remuneration when monitoring methods have been introduced. The specific form that the re-structuring takes usually involves substituting long-term incentive measures, such as stock options, for short-term absolute pay increases. However, Main and Johnson (1993) find no basis for accepting such an assertion.

Threat of Dismissal

Rather than motivate managers by internal devices, external market pressures particularly in the labour market may motivate managers[38]. The threat of dismissal complements the idea of corporate governance. Since the boardroom committee is responsible for evaluating managerial performance, another one of its functions must include initiating change in the event of poor firm performance through managerial dismissal. Evidence suggests that the probability of managerial turnover, controlling for mandatory retirement and type of dismissal[39], increases as stock market performance falls (Coughlan and Schmidt, 1985; Cosh and Hughes, 1997; Conyon 1998). However, the credibility of the threat depends on both the composition of the committee (i.e., number of non-executive directors) and the size of the committee - the larger the committee, the less likely it is that turnover will occur. In addition, there needs to be a readily available pool of appropriate replacements outside the organisation.

Empirical studies suggest that the rate of managerial turnover is low[40]. Conyon (1998) finds that there were 102 departures from 184 companies between 1986 and 1994. Of those departures, only 40 could be considered to be the result of dismissal. In a sample of 64 companies in the UK electrical engineering industry, Cosh and Hughes (1997) find that 60 per cent changed manager (CEO) during the sample period (1989-

[37] Main and Johnson's findings may be due to omitted variable problems (unobserved firm effects).

[38] Managerial behaviour can also be disciplined through competition in the product market, the threat of takeover and the threat of bankruptcy. The latter two market discipline devices convey additional agency relationships between the manager and the bank, and the manager and new owners.

[39] In practice it is often difficult to establish the reasons for departure. Managerial separations in corporate organisations, much like the sports industry, are often disguised: "Smith leaves by mutual consent", or "Smith resigns", often mean dismissal.

[40] This is certainly not the case in the football industry where the frequency with which clubs change manager is one of its most prominent features.

1994), but only one-third of managers were dismissed for poor performance. The main reason for separation in most studies seems to be retirement.

1.5 Efficiency Wage Models

The pay-performance models discussed in Section 1.4 suggest that the wage of the manager ought to vary with the performance of the firm. Efficiency wage theorists, on the other hand, suggest that incentives can be introduced using fixed wage contracts. Workers effort or productivity depends on the *level* of wage rather than how the wage is paid. It is often the case that piece rate wages are impractical because, as we have seen above, observing worker output is difficult. A further benefit of paying an efficiency wage is that it circumvents sub-optimal solutions brought about because of manager risk aversion. By offering wage premiums (economic rents) in excess of the market-clearing wage, the cost of job loss increases. Apart from reducing managerial shirking (see below), the approach identifies two other benefits of higher wages. Firstly, it may be costly to allow an employee to quit because the expenditure incurred in training the individual would now be borne again in the training of the new employee. This is the labour turnover interpretation of efficiency wages. Secondly, workers who feel they are being treated fairly, in comparison with other employees doing a similar job, will be more productive and less likely to involve themselves in unproductive activity. This is the morale effects interpretation of efficiency wages.

Shapiro and Stiglitz (1984) provided the foundations of the shirking model. As in the P-A model, the manager derives utility from remuneration and disutility from effort. Therefore, reduced effort will occur if the benefits of shirking exceed the expected costs of shirking:

$$U_M^S > c(w - \overline{w}) \tag{1.12}$$

where U_M^S is the expected utility from shirking and the probability of being detected shirking is c. We assume, for the time being, that if the manager is caught shirking he/she is fired with certainty (and that there are no job displacements for exogenous reasons). The wage paid to the manager is w, and $\overline{w}$ represents the wage in the next best alternative employment (net of search costs). The economic rent paid to the manager is the difference between w and $\overline{w}$. The possibility of earning rents increases the costs of shirking. Whether the manager shirks also depends on the probability of being caught. By making equation (1.12) an equality and re-arranging in terms of w, we find the minimum wage (w_*) necessary to induce the manager to work:

$$w_* = \frac{U_M^S}{c} + \overline{w} \tag{1.13}$$

Equation (1.13) is known as the no-shirking constraint (NSC). The minimum wage necessary to induce the manager to work is dependent on the amount of utility the manager gains from shirking, the probability of being detected and the next best alternative wage. Apart from offering rents as a discipline device, the firm may be able to alter the probability of detection by increasing the level of monitoring. However, monitoring is often costly so the payment of efficiency wages or increasing the level of monitoring can be considered as substitutes. A third way, and one that is not under the control of the firm, is to alter the wage in the next best alternative employment. At the extreme, if the next best alternative is unemployment, such that the value of unemployment is the product of unemployment benefit and increased leisure time, then the level of rent required to induce the manager to work will be lower, *ceteris paribus.*

Relatively few studies have attempted to test the importance of efficiency wages using firm-level data. Campbell (1993) finds some evidence that firms experiencing high turnover costs experience lower quit rates. Leonard (1987) tests the shirking model by observing whether there is a trade-off between monitoring (as measured by the supervision ratio) and higher wages, and tests the labour turnover model by observing whether there is a trade-off between wage and quit rates. He finds that neither seem to account for the wage dispersion observed. On the other hand, Groshen and Krueger (1990) using hospital employee data do find evidence that wage rents and levels of monitoring are substitutes. Furthermore, using aggregate data Krueger and Summers (1988) also suggest that efficiency wages are a more pervasive reason for high wages than union threats, or compensating differentials (such as hours of work, overtime levels and working conditions).

Given the contrasting conclusions offered by the studies outlined here and in Section 1.4 it is tempting to assume that there is little evidence to suggest that incentives are actually written into managerial contracts. However, one reason for the inconsistencies that have arisen in the empirical analysis of incentives is because the nature of the contract (and, therefore, motivation) depends on a wide-ranging set of factors: the internal structure of the firm, external constraints and preferences of the manager. Thus, we cannot expect the pay-performance coefficient to be identical for all firms. Nor can we expect the pay-performance coefficient to be the same for every manager in the same firm. In fact, it becomes clear why different studies offer different conclusions. The clearest evidence on this has been presented by Jensen and Murphy (1990b) who suggest that the pay-performance coefficient ranges from -0.007 to 0.447 in their study of managerial pay in 1,400 public companies. Garen (1994) explains such wide variations in terms of the firm's variability of returns and environmental risk. He argues that these factors account not only for the variability in the pay-performance measure, but also its low size (35 per cent of firms in Jensen and Murphy's sample had a pay-performance coefficient between 0 and 0.002). In addition, the size of the firm must also be taken into consideration. Information asymmetries are likely to be less prevalent in smaller firms where the owner is more closely involved in the day-to-day operations. As a result, the potential to shirk on the part of the manager is significantly reduced[41].

1.6 Measuring Ex Post Effort: "Do Incentives Matter?"

The theories of pay-performance and efficiency wages state that suitable incentive arrangements should be introduced into the wage determining process. Ex ante contracts based on incentives should align the effort level of the manager with that expected by the owner. Whilst there seems to be some, albeit not substantial, evidence that wage incentive and monitoring devices are used these measures alone do not tell us whether effort and performance actually increases ex post. They only tell us it is more likely to.

[41] Shirking is only likely to be completely eliminated in owner-manager firms due to the coalition of ownership with control.

Very little work has been directed towards analysing whether incentives matter. Part of the problem is due to an absence of individual data on performance and contracts. Three studies have, however, managed to appropriate such data. Lazear (1996) considers how the move from fixed wages to piece rates affects the performance of workers who install auto windshields. Paarsch and Shearer (1996) carry out a similar analysis on Canadian tree planters and Fernie and Metcalf (1996) compare the performance of British jockeys who are paid a fixed wage against those that are paid on the basis of winning races. All three studies find favour with the hypothesis that pay incentives improve performance.

A few managerial-based studies are contained within a special issue of Industrial and Labor Relations Review (volume 43, 1990). Unlike three studies listed above, the studies here use firm performance measures (of the kind outlined in Section 1.4) to again proxy for managerial performance. Using conditional probability theory (in the absence of repeated observations of firm performance), Abowd (1990) finds evidence for improved future performance following increased pay-performance sensitivity and the analysis is stronger for market-based measures than for accounting-based measures. Leonard (1990) using a substantially larger data set (20,000 managers) compares the performance of firms that use incentive structures with those that do not. Leonard finds that there is little difference between the performance of firms that use pay for performance incentives than those that do not. Instead, pay seems to be more a function of position within the company than to company performance per se. This is likely to have more to do with the limitations of the data than a serious question of the pay-performance model because Leonard finds pay incentive schemes existing in 90 per cent of the firms sampled.

Rather than use output measures, two studies have attempted to measure effort itself. Drago and Heywood use survey data on all types of job holders. The data provides information about job conditions and job performance (i.e., effort). Because the data is qualitative, Drago and Heywood (1991) model effort using a dummy dependent variable (1 for high effort; 0 for little or no effort). They conclude that higher effort is positively related to higher remuneration. In addition to testing the pay-performance relationship, Drago and Heywood also consider the ease or re-employment and the size of the firm as additional incentive factors. Both are found to exhibit a negative relationship with the level of effort. Therefore, the easier it is to obtain a job of a similar nature for similar pay and the greater the absolute size of the firm the lower the level of effort.

A major drawback of Drago and Heywood's model is that it applies to all types of workers within the firm, not just the manager. A more significant drawback is that effort is measured subjectively through voluntary response questionnaires. Foster and Rosenzweig (1994) take a rather novel approach in an attempt to measure performance objectively. They measure effort as a result of weight changes in agricultural workers. For a similar calorie intake, those workers who are on piece rate wages tend to lose more weight than those on fixed wages. Here, higher weight loss is associated with greater effort. Again, however, management is not the unit of observation.

It is important to bear in mind that improved effort and performance following the introduction of incentives may in fact have nothing to do with incentives. Instead it may well reflect the issue of worker selection whereby less able workers leave the firm and are replaced by more able workers (Lazear, 1996). Hence, what at first sight appears to be performance-inducing incentives is actually the result of selection effects. Therefore, as well as incentives, we need to analyse the characteristics of the manager and how such characteristics affect performance.

1.7 Managerial Quality, Selection and Performance

The concern so far has been with the contractual nature of managerial employment. In our discussions on agency we assumed away the problem of managerial heterogeneity by looking at first-difference equations. Given the roles a manager carries out (Section 1.2), this is clearly restrictive: as well as motivation, managers differ in terms of ability and experience. In this section we introduce how the manager's characteristics influence performance and pay.

1.7.1 Human Capital Theory

Human capital refers to the skills and knowledge (of a productive nature) embodied in people. The embodiment takes either the form of intrinsic ability (known as innate human capital) based on natural ability and physical strength, or investment (acquisition) of human capital such as schooling and on-the-job training. Schooling refers to the production of training only. On-the-job training refers to training in conjunction with production. The skills developed through on-the-job training can either be specific to the current firm or transferable to other firms. Any training that raises the productivity of the individual at the firm providing the training and at other firms (by an equal amount) is classified as general on-the-job training. If training increases the productivity of the individual more in the firm providing the training it is known as specific training. In practice it is often difficult to distinguish between the two.[42]

There are two strands to the theory of human capital. One explores the rate of return on the investment in human capital, explaining why investment, such as schooling, takes place early in a person's lifetime. The second aspect and the one considered here, is the link between human capital and employee (managerial) productivity. The two strands are linked through the effect that human capital investment has on individual pay (Becker, 1964). Specifically, the relationship is as follows: human capital accumulation increases skills; these skills increase productivity; increased pay is the reward for higher productivity.

Wage Equations: Human Capital or Incentives?

Mincer (1974) proposes a test of the human capital and performance relationship using information on wage profiles. A positive relationship between human capital accumulation and wage growth is seen as an indicator of job productivity. Widely known as the Mincerian (log) earnings function this is:

$$Ln(w_i) = b_0 + b_1 SCH_i + b_2 TEN_i + b_3 EXP_i \qquad (1.14)$$

[42] Becker (1964) notes that the recruitment of military personnel offers an example that seems more clear-cut than in other sectors. Here some training is useful in the civilian sector (organisational skills, leadership), whilst other training (learning the techniques of being a fighter pilot or missile man) is of no relevance at all.

Advocates of human capital theory suggest that investment in education (*SCH*), tenure (*TEN*) and experience (*EXP*) will increase earnings (w) due to productivity gains. Furthermore, Mincer assumes that most education and training will take place when the worker is young because the present value of the benefits of education and training is higher. The amount of time the worker subsequently devotes to human capital investment (i.e., on-the-job training) declines with experience. For football managers there is a general absence of further and higher education qualifications and only limited formal training. Most football managers tend to rely on playing experience and 'learning by doing'. As age proxies for experience (both formal and on-the-job) this gives an age-wage profile that is distinctly concave from below - earnings rise with age but at a decreasing rate. Kim and Polachek (1994) offer a recent example applied to panel data.

However, as suggested earlier, wage rents may be made to discourage management from shirking or quitting. If true, a positive age-wage profile may have nothing to do with human capital accumulation. The incentive alignment argument[43] suggests creating earnings differentials over an employee's career horizon because of monitoring costs and possible high turnover costs[44]. The differentials are structured so that pay is below productivity at the start of the career and then above productivity towards the end of the career (known in the literature as seniority wages). The prospect of earning more later on keeps the employee tied to the firm and reduces the temptation to shirk[45].

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[43] Effectively an efficiency wage argument.
[44] Other explanations include a self-selection device to discourage movers (Salop and Salop, 1976) and job matching under imperfect information (Jovanovic, 1979). It may, however, just reflect workers' preferences.
[45] One important corollary is employer moral hazard. In age-earnings models, in which a wage is paid in excess of productivity for senior workers, the firm has an incentive to replace old workers with young workers who are paid less than their productivity (assuming the wage cost includes re-hiring and training costs). Tournament contracts (Lazear and Rosen, 1981) whereby the firm commits itself to a fixed- total wage bill, and the firm's concern for its reputation are two possible solutions to this problem.

Lazear and Moore (1984) provide evidence of such incentive-based wages by comparing the present value wage profiles of employed and self-employed employees. Here one class, the employed, require more monitoring than the self-employed class, who, according to the theory, require steeper wage profiles. Lazear and Moore find that the provision of incentives is indeed important in determining the steepness of wage profiles. More recently, Kotlikoff and Gokhale (1992) find evidence of incentive wage payments for (male) managers using present expected value of total remuneration and the present expected value of productivity.

In contrast Hellerstein and Neumark (1995), by comparing productivity profiles[46] and wage profiles of unskilled workers in Israeli manufacturing, find support for the human capital notion of productivity improvement; suggesting that the two profiles are statistically the same. In a related approach, Blass (1992) tests the tenets of human capital theory by comparing individual worker productivity and wage profiles in Major League Baseball. Blass determines the player's marginal revenue product (MRP) sequentially, using the methodology first adopted by Scully (1974). The impact the offensive or defensive performance of the individual player has on the team's output (measured as team wins) is calculated first, followed by the effect that this change in output has on club revenue (i.e., gate attendance, broadcasting receipts). The results indicate that the proportion of players that are overpaid increases with experience: 86 per cent of players with over 10 years of baseball experience are overpaid. In contrast, only 20 per cent of players with less than three years experience are overpaid.

With the availability of more detailed data sets, rather than analyse the age-wage relationship researchers have recently begun to address the specific impact of various human capital measures. At the forefront has been the link between specific training and the wage profile. In the studies of Brown (1989), Lynch (1992) and Bartel (1995), training is used as a proxy for productivity and is found to be a major cause of wage growth. All follow the first-difference procedure to eliminate unobserved ability problems (e.g., equation (1.11)) and self-selection biases (i.e., trainability)[47]. Of the three, Bartel's results are the most convincing. Firstly, because she uses data obtained from a firm's personnel department - the two other studies rely on employee responses, thereby creating a necessary dependence on individuals being able to recall the amount and type of training undertaken. Secondly, a single firm approach eliminates the difficulties in comparing training regimes across firms. One drawback, however, is that the conclusions cannot be considered as being applicable to other firms.

Even though these studies suggest that training increases wage growth via productivity improvements, incentive payments still cannot be ruled out. Following the period of training, higher wages could be paid because of the higher cost that arises if the employee subsequently quits. Brown (1989) attempts to eliminate the effect of contractual devices by introducing early tenure dummies. However, this implicitly assumes that contracts are of a long-term nature.

All of the above studies investigate human capital theory applied to the general workforce. Several studies have also analysed the impact of human capital measures and incentive mechanisms on managerial wage equations. These studies extend equation (1.14) to include firm-related characteristics such as profitability, sales (Hogan and McPheters, 1980; Kolluri and Piette, 1985), and other firm-related characteristics

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[46] The productivity profile was measured as a marginal contribution in a production function.
[47] Ashenfelter (1978).

(Johnson and Danson, 1996). By including firm performance measures and human capital measures, these studies seek to establish whether managerial pay is paid independent of managerial performance. This is the idea behind the signalling theory (see below). Whether signalling occurs depends on whether the performance variables (sales and profits) capture the full human capital effects of the manager. Given that it has already been established that firm performance is a noisy approximation to managerial productivity, the significance of the human capital measures may well be the result of productivity improvements. However, if the performance measures are reliable, the significance of the human capital aspects supports the signalling hypothesis[48].

1.7.2 Hidden Information and Managerial Sorting

Towards the beginning of the chapter, two sources of asymmetric information were mentioned: hidden action and hidden information. So far we have concentrated on the asymmetry of information that exists once the manager is in post (moral hazard). Information asymmetry also exists before the manager is appointed. Hidden information or adverse selection models suggest that managers are better informed of their true abilities than the firm which seeks to hire them. The sorting hypothesis[49] offers an explanation as to how owners make hiring decisions under conditions of uncertainty

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[48] A less noisy productivity measure is provided by Blass (1992). He also finds evidence that including the productivity measure in a wage equation for baseball players does not reduce the significance of the experience variables.

[49] There are two types of sorting. Firstly, where the manager sends an ability *signal* to the owner. Secondly, where the owner makes known the criteria required of potential managers by *screening* applicants.

about managerial productivity[50]. It also offers an explanation as to how managers can signal their potential productivity.

Signalling theory is the most common of the sorting models (Spence, 1973), and has mainly been applied to education. The theory states that rather than increase productivity, education acts as a screen to filter out (screen out) those with educational qualifications from those without (Arrow, 1973). Similar reasoning could also apply to labour market training experience. In either case, the informational flows are representative of a signal in the absence of perfect information regarding productivity measurement - those with educational qualifications and/or labour market training experience are seen as being more productive than their non-educated counterparts. In other words, potential employees use education to signal their productivity. Education and experience are not the only screening devices available to employers. Football managers are likely to signal their abilities through the quality of their playing career and quality of their managerial experiences to date. Interviews, questionnaires, psychometric tests and medical history records can also be used. However, unlike education and training experience, obtaining the relevant information from these sources may be costly.

Given this, the owner must make judgements about the relative merits or beliefs of the manager on the basis of this signal. Spence argues that this may lead to situations where the hiring decision results in higher wage payments independent of actual productivity because information about potential productivity is imperfect. In the extreme version of signalling, there is a zero correlation between the signal and productivity.

[50] Managers often hire other managers. For simplicity, we continue to assume a single manager runs the firm.

Human capital theory and sorting theories make allowances for innate ability. Both expect a correlation between schooling and experience achieved and innate ability. However, it is difficult to measure ability. As outlined in Section 1.2, managerial ability refers to leadership, motivation and personality. Much of this is likely to be innate, and virtually impossible to quantify. One attempt to do so is to simply introduce IQ scores and family background measures into the Mincerian earnings function (see Griliches and Mason, 1972). Alternatively, the effects of schooling can be realised by comparing individuals with the same "ability" (e.g., see Taubman's 1976 study of twins). The sorting explanation implies that ability determines schooling and labour market training. In addition ability differences between workers is not only present before human capital investment decisions are made, but such acquired ability has no effect on productivity[51].

Much of the empirical investigations of sorting have concentrated on the amount of schooling required for classes of occupations where signalling is likely to occur (i.e., employed sector) with those (such as self-employed) where signalling is not required. Evidence of signalling would be provided by increased years of schooling for the employed class, although there is little evidence in the literature to suggest this is true. Wolpin (1977) finds the level of schooling of the two classes are similar and, even more surprising, has a larger impact on the earnings of the self-employed. Johnes (1998) also finds little evidence of sorting between employed and self-employed categories. In addition, Johnes suggests there is little correlation between tenure (measured by age) and the decline of the rate of return from education - the longer the employee is at the firm the more likely the firm is able to acquire information regarding the worker's

[51] This viewpoint raises suggestions that there is over investment in education for example. This is clearly at odds with the macroeconomic data which suggests that there is a strong positive correlation between levels of education and per capita gross domestic product.

productivity. This latter result may well be the product of an incentive alignment argument, consistent with the results of Riley (1979). Finally, as a hiring mechanism Albrecht (1981) finds no evidence that in the absence of information the probability of being hired does not tend to rise with extra education.

The inconsistencies in the findings may be because the categories are inappropriate, possibly because the distinction is not always clear-cut (e.g., Riley splits the categories *after* observing the lifetime earnings). Furthermore, even if clear categorisation can be achieved, a sample selection bias may occur because the self-employed may be self-employed because they under-invested in education. Knowing that the signals they provide to potential employers are likely to be inadequate, they become self-employed instead. Similarly, how can information sources in the hiring process be measured and how reliable are they in practice?

Using wage equations does not allow us to discriminate between human capital and sorting explanations as both studies yield similar equilibrium outcomes. As we stressed earlier, there are several different definitions of pay. In addition, it is possible that payment can be non-pecuniary (i.e., praise, or company perks such as cars and discounts) as well as pecuniary. Non-pecuniary payments will underestimate the actual utility that the manager derives. In other words, pay is only an approximation to managerial utility[52].

Individual productivity measures would help end the debate. However, in the absence of capturing ability differences we do not know whether the productivity

[52] It is probably a reasonably good approximation because rational individuals prefer cash payments to payments in-kind.

improvement is associated with education and labour market training itself, or with the ability aspects associated with self-selection. Tracking a panel of managers may help resolve such differences since we can observe how changes in experience affect changes in managerial performance.

1.8 Measuring Managerial Performance

All of the studies discussed so far have used indirect measures of managerial productivity (accounting data, firm sales, or market-based performance measures). It is clear that these measures are noisy approximations to actual managerial performance because they include numerous random factors that are not under the control of the manager. In addition, they fail to take into account the contribution of other inputs (i.e., non-managerial workforce, physical and financial capital). Individual performance measures can help to establish whether human capital investment and incentives affect performance, and can be categorised as either subjective measures or objective measures.

1.8.1 Subjective Measures of Managerial Performance

Subjective evaluations involve peer assessment of an individual's performance. A common approach in testing the human capital interpretation of performance is to compare the human capital variables in a wage profile with those same variables in a productivity profile (Medoff and Abraham, 1980; Medoff and Abraham, 1981; Holzer, 1990). Alternatively, one could observe the effect of entering the productivity measure as an additional determinant (i.e., in addition to human capital measures) in a wage equation (Medoff and Abraham, 1980; Medoff and Abraham, 1981)[53]. In those studies that compare wage profiles with productivity profiles, if productivity is the sole determinant of remuneration then the human capital coefficients in a wage equation should be the same as the human capital coefficients in the productivity equation. In terms of entering productivity in addition to human capital measures in a wage equation, if productivity is determined by human capital accumulation, it would be expected that the introduction of the individual productivity measure into the wage equation would make the estimated coefficients of the human capital measures zero[54].

Medoff and Abraham (1980) analyse both of these hypotheses using supervisor ratings from two American corporations as measures of performance for white male managerial and professional employees[55]. In the wage function the additional inclusion of performance ratings, whilst having a significant and positive effect on earnings, has no impact on the human capital measures of schooling, job tenure and job experience. Using multinomial logit wage and performance equations they also find that job market experience increases the likelihood of being in the worst performance category, whilst a lower level of schooling results in a higher performance but a lower salary. The results suggest that the relationship between human capital and productivity is absent; human capital accumulation results in higher pay but not because of productivity improvements. A possible solution to this, as demonstrated earlier, is managers typically have more discretion about their work than other employees do. Consequently, owners have to

[53] Subjective performance measures can also be used as an additional information source in contract design.
[54] These hypotheses have already been considered for indirect performance measures.
[55] They split the performance ratings into four categories:
(1) Not acceptable/satisfactory.
(2) Acceptable/good.
(3) Good/superior.

initiate incentive mechanisms to correct for such discretion (i.e., increase pay above the market-clearing rate). By itself, however, this does not resolve the issue as to why human capital measures have no effect on performance.

Holzer (1990) analyses wage and performance equations in a survey of American firms using data obtained from the Employment Opportunity Pilot Project (EOPP). In contrast to Medoff and Abraham, he looks at all types of employees, not just the managerial labour force, and finds support for human capital determinants of productivity improvements. However, on Holzer's evidence, human capital aspects "explain" wage differences better than productivity differences: an R^2 of around 50 per cent in the wage equation and 16 per cent in the productivity equation. Paradoxically, this supports the results offered by Medoff and Abraham. Holzer includes experience (measured in months), tenure (months) and training (formal and informal hours by management, supervisors or co-workers) together with education (high school or college), gender, union membership and size of firm in both pooled cross-sectional and first-difference equations[56]. Overall, Holzer finds the magnitudes of experience, tenure, and training are higher than schooling measures in both wage and performance equations.

In addition, the study directly introduces incentive schemes as an additional determinant of productivity by directly asking employers whether an incentive scheme was used. The evidence suggests that pay incentives have no effect on productivity. Kahn and Sherer (1990) provide more compelling evidence in their analysis of middle and upper-level managers. Their study is more appealing because they consider types of

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(4) Outstanding/excellent.

incentives (bonuses, merit pay and pay-levels) rather than just appealing to the existence of such measures[57].

In the most comprehensive study to date, Krueger and Rouse (1998) find that schooling and experience, rather than training, determines performance awards. Their study uses data from two companies, one in the manufacturing sector and one in the service sector[58]. Apart from performance awards, the study also considers the effects of training on the hourly wage, probability of turnover, probability of promotion[59], level of worker absenteeism and other subjective performance measures based on employee responses.

A number of criticisms have been directed at these and other papers which investigate productivity using subjective performance measures. Firstly, the results of studies that compare several firms are usually biased because it is likely that each individual firm is unique in their definitions of employee performance and training methods. Furthermore, the performance of employees is only comparable if they undertake similar roles and have similar responsibilities. For example more experienced workers may be asked to carry out more, or less, difficult tasks, and by doing so will generate higher or lower levels of productivity. The supervisors who carry out the evaluations may themselves be biased (i.e., understate performance to save on wage costs, for example). This is not a problem if they treat all members in this way, but will

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[56] Medoff and Abraham (1981) in a follow-up study also consider a first-difference model using longitudinal data with similar findings. In particular, whilst the wage increased over time, productivity fell.
[57] Furthermore, only 11 per cent of the firms sampled in Holzer's study made use of incentive pay.
[58] Performance measures used in the service sector only.
[59] Wise (1975) also considers promotional activity, this time as a measure of performance. By doing so, his study suffers from the same weaknesses as those studies that use training to proxy for job performance. Wise's study is interesting in one other aspect: unlike all other studies it is able to

be if they discriminate against some workers in favour of others (e.g., black versus white or experienced versus inexperienced).

Evidence of the appropriateness of these subjective performance measures has been considered by each of the above studies, usually by looking at the effect the subjective measure has on both the probability of being promoted (Medoff and Abraham, 1981) and on salary increases (Medoff and Abraham, 1981; Holzer, 1990). After controlling for human capital factors, the results seem to indicate that a higher performance rating improves the probability of being promoted and /or the probability of salary increases. It is possible, however, that the correlations between wages, promotion and productivity result from the evaluators giving high-wage workers, and workers in higher positions, higher scores.

1.8.2 Objective Measures of Managerial Performance

Studies that make use of objective measures of individual performance have been rare. As noted by Medoff and Abraham (1981):

> First the dimensions of an employee's current true value to his or her firm would have to be quantifiable. Second, either there would have to be only one dimension relevant for assessing the employee's true current worth or the researcher would have to know the proper set of weights or shadow prices to attach to each relevant dimension (p. 206).

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measure unobserved ability aspects (leadership qualities, imagination and initiative). Incidentally, these were all positively related to the rate of promotion.

The Navy has been the best provider of information on objective performance evaluators to date[60]. Horowitz and Sherman (1980) measure employee productivity by the number of hours specific pieces of naval equipment - boilers, engines, guns and missiles - are "downtime" (out of service). Controlling for other aspects which could cause failure (e.g., age of the ship and equipment, length of time since the ship was last overhauled and the absolute number of crew members) they find that experience at sea and experience on the vessel, qualifications gained in Navy school (schooling) and on the job (training) all perform well in the regression equation. Level of pay also seems to be an important factor.

Continuing the Navy theme, Kostiuk and Follman (1989) examine data on Naval Reserve recruiters, measuring productivity as the number of enlistments obtained within a month. Due to the limited distribution of the performance variable the model is estimated using a Poisson distribution. This time, schooling (nongraduate or college educated) does not seem to have a strong impact on performance. On the other hand, experience (measured by length of military and recruiting service) and pay are significant. Asch (1990) extends this type of analysis to include other aspects of incentives such as piece-rates, quotas, prizes and standards.

Maranto and Rodgers (1984) also make use of an objective measure of productivity this time in a study of wage investigators for an American mid-west state. The productivity measure is a wage recovery measurement variable based on the wage that an employer owes an employee. It is the job of the wage investigator to recover this wage for the employee. His/her ability to do this is expressed in their recovery experience and skill. The study not only analyses a pooled cross-sectional productivity

[60] See, also, the studies cited in Section 1.6.

equation, but in addition, controls for possible unobserved characteristics (i.e., ability of the wage investigator) in a fixed effects model and compares the effects of the human capital coefficients and the wage recovery measure in a wage equation. In each case, tenure (years of experience in the Wage-Hour Division) performs the best. The significance of other human capital aspects, education (measured as years of schooling) and experience (general labour market experience prior to appointment), depends on the model specification considered. Finally, although the study finds some support for the human capital - productivity relationship, the results are also consistent with Medoff and Abraham (1980).

More recently, researchers have started to make use of production functions in determining individual productivity (Hellerstein and Neumark, 1995; Black and Lynch, 1996). These studies continue to use firm output, but seek to determine the contribution of other firm inputs (i.e., stock of capital, cost of raw materials and so on) as well as worker characteristics (average educational achievement, formal training) and other firm-related aspects (such as level of union membership and other workplace practices). However, both of these studies are concerned with the effects of human capital on all employees within the firm. Indeed, with the exception of Medoff and Abraham (1980, 1981) and Kahn and Sherer (1990), none of the above studies measure individual productivity using the manager as the unit of observation. And both rely on measuring managerial performance using subjective criteria.

1.9 Summary

In this chapter we have demonstrated that a manager's performance is determined by incentives and ability (innate and acquired). The majority of previous studies use wage equations and indirect (firm) productivity measures to establish the link between pay and managerial performance. We also established that there is some evidence to suggest that managerial incentives are constructed to reflect both internal and external influences.

Wage equations have also been used in establishing the impact of human capital and ability aspects. Some studies assume that the wage proxies for productivity, but given that managerial incentives are necessary, this is clearly unreasonable. Other studies have considered the impact of indirect performance measures on these human capital measures in a wage equation. Most conclude that pay is determined by both productivity and non-productivity factors (i.e., efficiency wages and sorting theory).

The theoretical work of principal-agent analysis does not consider how managerial performance should be measured. However, it is likely that a more direct performance measure of managerial contribution would provide more information than the indirect measures considered above. Subjective performance measures suffer because they are not comparable across firms and not comparable in the same firm over time. Objective performance measures are better, but these have been difficult to operationalise. Generally, these studies compare human capital and/or incentive measures in both wage and productivity equations with the results tending to improve upon those that use indirect measures. In the next chapter we outline an alternative approach to generating an objective measure of managerial performance using production frontier methodology.

CHAPTER 2

PRODUCTION FRONTIERS: TECHNIQUES AND APPLICATIONS

2.1 Introduction

In Chapter 1 we suggested that the goals of managers and owners in modern organisations are likely to conflict because of the principal agent relationship that characterises organisations. There are two reasons for this. Firstly, if monitoring is costly it is possible that the manager will exert less than the maximum amount of effort, thus reducing the size of the residual available to the owner. For economists, one way to alleviate this problem is by aligning the objectives of the manager with that of the owner. Secondly, before the manager is hired the owner does not know which of the manager's characteristics will lead to improved performance, or he/she does not have full information about these characteristics. In the context of the football manager, a lower level of performance – either by exerting less than maximum effort or incorrect ability signals (i.e., bad job match) – will mean his team will win fewer games than it would otherwise win were he exerting maximum effort or the job match was optimal. If output (wins) is below the maximum possible it is likely that the manager is not expending maximum effort or there is a bad job match. In other words, he is inefficient (less than 100 per cent efficient).

In order to ascertain whether managers are operating at maximum efficiency we need a way of measuring the performance of the manager in relation to the 'best practice'. One way of doing this is to estimate a frontier production function. It is the aim of this chapter to review the literature on frontier production functions paying particular attention to the methods that are available for estimating individual managerial efficiency. In this context, we focus on the theory of the stochastic frontier production function and its applications particularly when using panel data. As an extension to the literature we consider the techniques used by researchers to explain variations in efficiency across firms and managers. Also, we review the literature that applies the production function and frontier production function methodologies to team sports. Finally, we consider the direction the theoretical and empirical analysis ought to take in the light of the discussion so far.

2.2 Production Functions and Production Frontiers

> In economic theory the production function is a mathematical statement relating quantitatively the purely technological relationship between the output of a process and the inputs of the factors of production, the chief purpose of which is to display the possibilities of substitution between the factors of production to achieve a given output (Shephard, 1970, p. 3).

A production function describes combinations of all technically feasible processes available in a given time period. Each process is represented by a relationship between inputs and the resulting output. The inputs or factors of production can be classified as: land, labour and capital. Land includes all natural resources which can be used for productive purposes (e.g., natural resources such as farm land, mineral deposits). The labour input includes all the firm's employees (managerial and non-managerial), while capital can be described as either physical capital (e.g., machinery and buildings) or financial capital (e.g., bank loans and equity finance). Technology is usually characterised by a single, scalar output measure and the firm has an economic objective to maximise output or profit, or minimise cost. In the context of football, team performance is output and the inputs are players and management (see Chapter 4).

In economic parlance the firm is the economic agent which transforms a given set of inputs into a given set of outputs[1]. However, as we saw in Chapter 1, management is the decision-making unit that is often employed to carry out such operations. Our objective later on is to analyse the contribution of the manager separately from that of the players. However, for most of this chapter (to Section 2.5) the term "firm" will be used generically when discussing the frontier production function literature.

All of the possible processes represent the production set and within this set there will exist a unique combination of inputs corresponding to a maximum level of output. Alternatively, it may denote a minimum input combination necessary to achieve a particular level of output. Both define the limit of technological possibility. Over time, technical progress has the effect of moving the production set upwards. In the literature, a function that maximises output for a given combination of inputs (minimises inputs for a given level of output) is known as a frontier production function or, more succinctly, a production frontier.

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[1] An important consideration which is often ignored is the "usefulness" of the inputs and corresponding output(s) in the specified model. This requires identifying the right economic objective and incorporating all the correct inputs that are appropriate for the output measure considered. As will be demonstrated later in this chapter, most applications suggest that incorporating a random error term should to some extent eliminate this problem. Chapter 6, in part, investigates the effects of alternative output and input measures on efficiency levels.

When we observe several different firms we see that some of these firms do not operate on the technologically feasible boundary. Instead, some firms are likely to produce an output level below it, or use "too many" factors to produce the output that corresponds to a position on the boundary. These firms are technically inefficient in the sense that efficient firms use fewer inputs to produce the same output or they achieve a greater output level from the same level of factor inputs. Neoclassical production functions "ignore" sub-optimal solutions thereby excluding the notion of inefficiency.

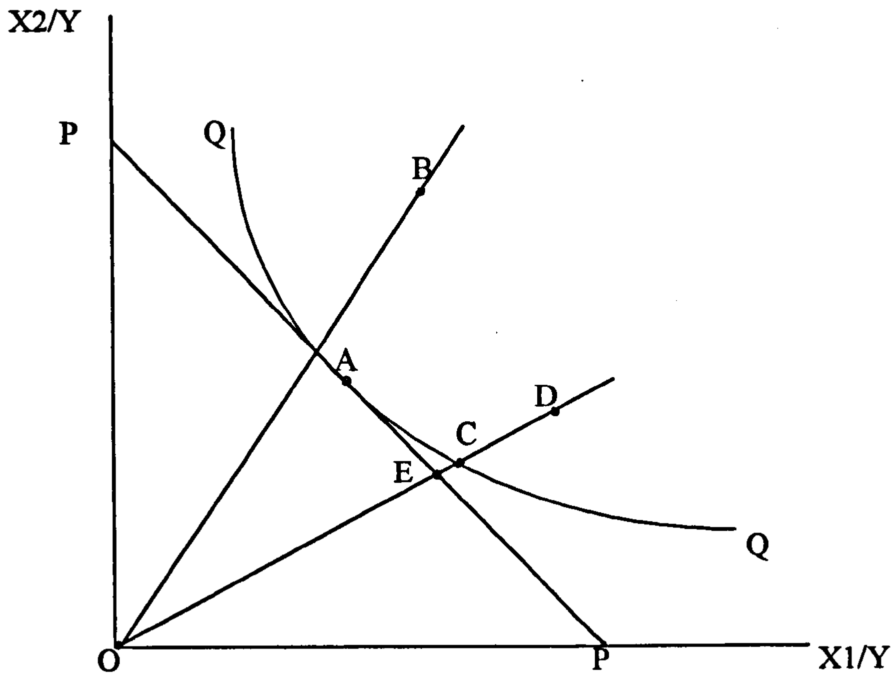
The production frontier approach acknowledges that many firms may be inefficient (operating below the frontier - output orientation; or above the frontier - input orientation) because of incomplete information, input quality differentials and so on. The production frontier approach estimates both the frontier (boundary) and the location of the inefficient (non-boundary) firms by comparing the two states. The determination of the production frontier together with the estimation of observed efficiency is the main concern of this chapter.

To begin with let us consider a geometric interpretation of a frontier production function in input orientation. For simplicity, assume that there is a single output measure (Y) which is determined by combinations of two inputs (X1 and X2). Also assume that the frontier technology is characterised by constant returns to scale, allowing QQ to represent the unit isoquant[2]. This is shown in Figure 2.1. Both points A and C are technically efficient as they lie on the unit isoquant (QQ). This is the same as the production frontier since by definition no points can lie below QQ. Firms can be compared by constructing a ray through the origin that extends beyond the frontier to

[2] Constant returns to scale implies that $1 = f(X1/Y, X2/Y)$. $X1/Y$ represents the horizontal axis and $X2/Y$ represents the vertical axis.

locate the firm in question. The level of efficiency is then measured as the ratio of the point from where the ray passes the unit isoquant (technical efficiency point) or isocost line PP (allocative efficiency[3] point) to the observed point. For example, consider firm D. Firm D is inefficient because it uses more inputs of X1 and X2 than is required for the unit output (at C). Technical efficiency is measured as OC/OD; it is the ratio of the amount of X1 and X2 needed to produce Y, to the amount of X1 and X2 actually used to produce Y. If this ratio is 0.5 then firm D is using twice as many inputs as it needs in order to operate efficiently. Similar arguments can be made for allocative efficiency. The allocative efficiency level of firm D is OE/OC[4] because the cost at E is the same as at A. Total (economic) efficiency (i.e., allocative plus technical) for firm D is therefore OE/OD.

Figure 2.1 A Production Frontier: Measuring Efficiency



[3] Allocative (or price) efficiency refers to the proper combination of the inputs given their relative prices. Any point along the isocost line PP is allocatively efficient.

[4] Firm B too is neither technically nor allocatively efficient. Firm C is technically efficient but not allocatively efficient. Only firm A is economic (technical and allocative) efficiency. The remainder of this chapter, and the rest of the thesis, concentrates on the measurement of technical, rather than allocative, efficiency. Hence we focus on production functions and frontiers rather than profit or cost

2.3 Estimation Methods

At the theoretical level both production functions and production frontiers exhibit certain technological properties. In no particular order these are monotonicity, quasi-concavity and differentiability. The monotonicity axiom states that increasing the number of inputs can never decrease the level of output (i.e., positive marginal products). This rules out irrational behaviour on the part of economic agents. Quasi-concavity means that the law of diminishing marginal productivity holds. Finally, differentiability implies that the production is well-defined and is not discontinuous. This means a specific functional form is usually required to represent technology. Often technology is considered homogeneous of degree zero or degree one (linear homogeneous) and homothetic. The importance of these two concepts is in the restrictions they impose on the marginal rate of technical substitution (MRTS); namely the MRTS is independent of the level of production.

Farrell (1957) provided the seminal work on production frontiers. Until then most empirical investigations of production tended to concentrate on the specification of appropriate functional form (e.g. Cobb and Douglas, 1928), disregarding the possibility of inefficiencies in production. Farrell proposed that the production frontier, of the kind presented in Figure 2.1, could be constructed using linear programming (non-parametric) techniques and observed levels of technical efficiency could be determined as deviations of observed performance from best practice performance. This approach is now more commonly known as data envelopment analysis (Charnes *et al.*, 1978)[5].

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functions. The interested reader should consult Bauer (1990) for a review of alternative frontier formulations.

[5] Data envelopment analysis (DEA) parallels the econometric approach taken here. Seiford (1996) provides a comprehensive guide to the literature in this area. The DEA method is particularly useful

In this thesis, however, we concentrate on the econometric (parametric) approach. There are two reasons for this. Firstly, non-parametric techniques suffer because of the inability to implement statistical testing. Secondly, relatively few parametric studies have analysed possible determinants of efficiency. In the next two sections we examine the estimation procedures available and consider the empirical applications.

2.3.1 Deterministic Frontiers

Early developments in the parametric literature focused on linear programming methods. Aigner and Chu (1968) considered the estimation of a homogeneous Cobb-Douglas frontier production function in input/output space as a linear and quadratic programming problem. Their approach was a significant improvement on Farrell's early work because it did not rely on constant returns to scale[6]. Schmidt (1976) proposed that another estimation procedure, maximum likelihood (ML) estimation, could be used if specific distributional assumptions concerning the efficiency term were introduced. In particular, Schmidt showed that efficiency follows an exponential distribution for the linear programming problem and a half-normal distribution for the quadratic programming problem.

For both the linear programming and econometric approaches, the deterministic equation takes the following form:

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when multiple output measures exist (see, Johnes and Johnes, 1995) and has been used in a wide-ranging number of applications (see the numerous studies contained in Charnes *et al.*, 1994).

[6] Questions regarding the appropriate functional form of technology are discussed later (Section 2.4).

$$Y_i = X_i\beta - U_i \quad (2.1)$$

where Y_i is the output of the i-th firm; X_i is a vector of inputs used by the i-th firm including an intercept term; β is a vector of unknown parameters with β_0 added as a first element; and U_i is a non-negative variable and accounts for inefficiency in production so that Y_i is bounded from above.

The main drawback of the deterministic approach is that by assuming the entire deviation from the frontier is caused by a lack of efficiency, it cannot account for statistical errors - measurement or otherwise - that commonly occur in statistical models. Timmer (1971) attempted to address the problem by estimating the frontier after removing a percentage of the observations. However, there seems to be no theoretical basis for the elimination of these observations. Timmer chose 3 per cent but this is entirely arbitrary. In effect Timmer's approach simply adjusts the data for the effects of outliers, and whilst it is an improvement on the "pure" deterministic model, his approach remains deterministic with the frontier estimated from a subset of the original sample.

2.3.2 Stochastic Frontiers: Cross-Section Data

As mentioned above, the motivation behind the development of the stochastic frontier was the argument that the variation in firm performance is not simply the result of efficiency differences. The deterministic frontier will produce specification problems if there is considerable measurement error or omitted variables (i.e., factors which cannot be controlled or accounted for). Ideally, the efficiency component should be made up of events under the control of the firm. Random factors - events not under the control of the firm - should be confined to a statistical noise term found in any econometric model. Allowing random variation across firms to be independent of efficiency, such that the random element can be above (positive random error) or below (negative random error) the deterministic frontier suggests that each firm has its own frontier rather than a common frontier as is the case with deterministic models.

The stochastic production frontier (or composed error model) was first introduced (independently) by Aigner *et al.* (1977), Battese and Corra (1977) and Meeusen and van den Broeck (1977) and is formulated as follows:

$$Y_i = X_i\beta + (V_i - U_i) \qquad (2.2)$$

As in equation (2.1) there is a one-sided efficiency term (U_i), but now there is a symmetrical component (V_i) measuring the effect of statistical noise. Thus, the error term (V_i - U_i) is composed of a purely random element and an efficiency element. Equation (2.1) can be treated as a special case of equation (2.2) where $V_i = 0$, whereas if $U_i = 0$ the model reduces to the "average" production function (i.e., OLS estimation).

The statistical noise term is assumed to be independently and identically distributed (iid) and follows the normal distribution with zero mean and finite variance[7]. The efficiency term, as in the deterministic model, is one-sided (non-negative) and usually assumed to be half-normally distributed with zero mean and finite variance[8]. Alternatively, it can be estimated using an exponential distribution. Other models suggested in the literature, although yet to be tested empirically, include the gamma

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[7] $V_i \sim N(0, \sigma_V^2)$.
[8] $U_i \sim N(0, \sigma_U^2)$.

distribution (Greene, 1990) and the generalised method of moments (Kopp and Mullahy, 1990).

Stevenson (1980) proposes a generalisation based on a half-normal distribution truncated at zero but with possibly nonzero mean (commonly known as the truncated-normal distribution[9]). The argument follows that there is no real justification in assuming the mean value should occur at full efficiency (i.e., at zero). As Stevenson suggests, "...[the] specifications are based on an implicit assumption that the 'likelihood' of inefficient behavior monotonically decreases for increasing levels of inefficiency" (p. 58). Indeed, such a presumption is unlikely to hold for economic institutions or individuals (managers in particular) within these institutions given the discussion in Chapter 1 on the characteristics and incentives of managers and the diversity of firms. Unlike the previous two generalisations, Stevenson's approach has been tested empirically and contains the half-normal distribution as a special case.

Estimation of the stochastic frontier production function may be obtained using either corrected ordinary least squares (COLS) or maximum likelihood (ML)[10] techniques. COLS essentially displaces the estimated OLS intercept upwards until one residual is zero and all the others are negative[11]. ML estimation makes adjustments to both the intercept and slope parameters in estimating the frontier. The implication of this is as follows. The COLS method implies that the technological aspects of efficient and inefficient firms are identical. In other words, efficient producers are no more efficient than their inefficient counterparts on the basis of scale and substitution effects. In

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[9] $U_i \sim N(\mu, \sigma_U^2)$.

[10] ML estimation requires a numerical maximisation of the likelihood function, details of which can be found in Chapter 5.

[11] More precisely, this means adjusting the intercept term by $E(U_i)$ derived from the (higher) moments of the OLS residuals. For a readable treatment see Greene (1997b).

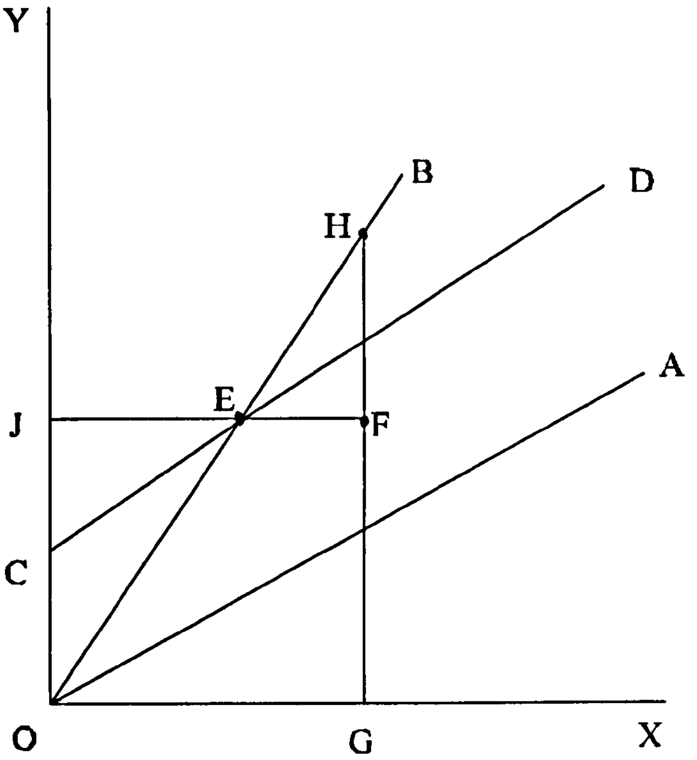
contrast, ML gives greater emphasis to the more efficient firms in the placement of the frontier[12].

These two approaches are analysed geometrically in Figure 2.2. Total input usage is now measured on the horizontal axis (X) and output is measured on the vertical axis (Y). Consider a scatter plot of points, which produces an estimated OLS regression shown by the line segment OA. The residuals would be placed above and below the line segment in a way that minimises the sum of squares. This line represents the "average" production function as estimated by the usual least-squares method.

Now consider point E as a hypothetical point representing the largest positive residual. The COLS production frontier is found by shifting vertically the line OA until it intersects point E. Under this analysis E is considered as the best-practice (most efficient) firm operating at 100 per cent efficiency because it lies on the COLS frontier, represented by the line segment CD.

[12] Similar arguments can be applied to panel data models (see Section 2.3.3).

Figure 2.2 Estimating Efficiency: COLS versus ML



Alternatively consider estimating the ML frontier. As mentioned earlier, the ML estimation procedure often results in a different intercept and a different slope compared to the COLS method. For simplicity we assume the line segment OB represents the ML frontier. The fact that OB intersects E is purely coincidental, and is done to ease exposition[13]. What is clear from the diagram is that the choice of estimator becomes important in terms of the level of efficiency that a particular firm achieves. For example, firm F is more efficient (i.e., closer to the frontier) under the COLS estimation procedure compared with the ML estimator[14].

[13] In the statistical analysis of Chapters 6 and 7, it is generally the case that no manager operates at maximum efficiency.

[14] One further aspect demonstrated in Figure 2.2 deserves consideration. As the production frontier is in input-output space the degree of efficiency (using the ML frontier, for instance) can be measured as either the ratio GF/GH (output increasing) or JF/JE (input decreasing). The two measures will give different inefficiency levels except in the case of constant returns to scale (e.g. Atkinson and Cornwell, 1994). Here preference is given to the output increasing interpretation of inefficiency.

The choice between COLS and ML, therefore, depends on what the analyst requires. If all one requires is an estimate of relative efficiency, and all firms have similar production functions (i.e., there are no scale or substitution effects), the OLS adjustment method can be used. For finite samples, Olsen *et al.* (1980) find no significant difference in the two estimators. However, ML is to be recommended when large sample data exists (COLS is not as asymptotically efficient as ML), and when the contribution of the efficiency component to the total composed error term is large (Coelli, 1995).

The placement of the stochastic production frontier is not a trivial matter. It requires the derivation of $Y_i = X_i\beta + V_i$ (i.e. $U_i = 0$). In practice we only observe the composed error (V_i - U_i) which means that each individual firm has its own production frontier depending on the magnitude of the random error term. For instance, the deviation of point F from point H in Figure 2.2 is composed of efficiency and purely random elements. In order to derive an output-increasing estimate of efficiency for F we need to decompose the noise element from the efficiency element. More formally, individual technical efficiency (*TE*) is calculated as:

$$TE_i = \frac{X_i\beta + (V_i - U_i)}{X_i\beta + V_i} \qquad (2.3)$$

Equation (2.3) measures inefficiency as the output that the firm produces relative to the output that it could produce, using the same input mix, were it fully efficient. The problem is in estimating the denominator.

Initially it was thought that individual efficiency could not be observed. Early empirical applications (e.g. Lee and Tyler, 1978) only report mean efficiency for the whole sample, measured as the average of the observed composed error or, following Aigner *et al.* (1977), $\sigma_U \sqrt{(2/\pi)}$. The problem of decomposing the individual residuals into their two components was eventually solved by Jondrow *et al.* (1982) using conditional probability theory. They proposed that the efficiency term could be estimated conditionally on the value of the composed error term. In other words it involves inferring the value of U_i given the value of V_i - U_i. The mean or modal value of the conditional distribution then provides an estimator of individual efficiency. Jondrow *et al.* provide formulae for both the half-normal and exponential distributions. More recently, Greene (1993) has derived equivalent expressions for the truncated normal and gamma distributions, whilst Battese and Coelli (1988) have provided a modification of the estimator when the dependent term is non-linear.

2.3.3 Stochastic Frontiers: Panel Data

Although the composed error term (V_i - U_i) can be estimated consistently, the efficiency term, although unbiased, is not consistent. This is because the conditional distribution estimates of U_i do not converge to the true value and the variance remains nonzero even for large sample sizes (see Greene, 1993). Furthermore, in order to derive these estimates distributional assumptions are required. The problem is that different distributional assumptions for U_i give different results[15]. For example, Lee (1983) compares the half-normal and truncated normal distributions for U_i using Lagrangean Multiplier (LM) tests. He finds that the correct distribution is case dependent: in the Columbian food products industry the truncated normal distribution is preferred; in the

[15] Different input and output measures are equally likely to lead to different results. This is explored further in Chapter 6.

Indonesian weaving industry the half-normal distribution is accepted. On the other hand, Greene (1993) finds the rankings of firms in the American domestic airline industry under half-normal and exponential distributions remain relatively unchanged: the rankings are the same for 67 per cent of firms. Of those firms whose rank differs, only two have a difference greater than one[16]. Consequently, the clear message here is that the appropriate distribution should be considered on a case-by-case basis.

With the availability of panel data these potential problems can be eliminated. Panel data[17] refers to a cross-section of firms or individuals that are observed over several time periods. In effect, estimation combines cross-sectional and time series data[18]. If we denote N as the number of firms and T as the number of time-periods, then if N is large and T = 1 we have cross-sectional data (or pooled data) and proceed to estimate as in Section 2.3.2. If N = 1 and T is large we have time-series data. Panel data occurs if N > 1 and T > 1. As we will see, estimation often requires N to be large and T to be small.

The panel data equivalent of equation (2.2) is:

$$Y_{it} = \beta_0 + X_{it}\beta + (V_{it} - U_{it}) \tag{2.4}$$

The model is the same as before, except t indexes time periods and β_0 is the intercept term so that the vector of inputs no longer includes an intercept. This is done to ease exposition in the analysis that follows.

[16] Contrast this with the results comparing the deterministic production frontier with the stochastic production frontier (Greene, 1993).

Since each firm is observed on several occasions better estimates of efficiency are likely to be obtained. The specification of efficiency can either be time-invariant or time varying - depending on whether efficiency is considered permanent or transitory. In addition, the model can be estimated assuming fixed effects (FE) or random effects (RE). FE are commonly estimated using the within estimator or the dummy variable approach. RE can be estimated using generalised least squares (GLS) or maximum likelihood (ML) providing we re-introduce distributional assumptions about U_{it}. A hybrid of FE and RE, the Hausman-Taylor (H-T) estimator, is another possibility.

Time-Invariant Efficiency

For the time-invariant model, equation (2.4) is re-specified as follows:

$$Y_{it} = \beta_0 + X_{it}\beta + (V_{it} - U_i) \tag{2.5}$$

The efficiency term in equation (2.5) is written U_i so that each firm's efficiency is assumed not to vary over time (as in the specification of equation (2.2)).

The FE approach treats efficiency as firm-specific constants. The advantage of this approach is that it allows efficiency to be correlated with the inputs of the production function. In contrast, the RE approach (using either GLS or ML) implicitly assumes efficiency is uncorrelated with the other regressors. If the firm knows its level of efficiency then this should affect the level and mix of its input choices. In the context of

[17] Sometimes referred to as longitudinal data.
[18] This is commonly referred to as pooling the data.

football, the manager may change his team's formation, drop poorly performing players, or even operate in the transfer market to improve team performance[19].

Estimation of the FE model follows either the least squares dummy variable approach (Schmidt and Sickles, 1984) or the partitioned least squares estimator method so that the inputs and the output are transformed into mean deviations (Hallam and Machado, 1996). The choice between the two seems to depend on the available degrees of freedom. If the number of firms is limited and number of time periods is small the mean deviations approach should be used[20].

For the least squares dummy variable (LSDV) approach, the transformed version of equation (2.5) can be written as:

$$Y_{it} = \beta_0 + X_{it}\beta + D_i\kappa + V_{it} \tag{2.6}$$

where D_i is a vector of dummy variables having a value of one for the *i*-th firm and zero otherwise and κ are parameters to be estimated[21]. If degrees of freedom allow, technical change can be entered using dummy variables (i.e., value of one for the *t*-th year and zero otherwise). U_i is found by assuming the largest dummy variable value is 100 per cent efficient. The efficiency of the other firms is found as deviations from the optimally performing firm. Formally:

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[19] This is likely to lead to the problem of simultaneous equation bias. To circumvent this problem we include players purchased mid-season in the team quality measure (see Chapter 5 for details).
[20] Formally, the mean deviation approach only requires a matrix inversion of order K-1 (K being the number of explanatory variables), rather than order N + (K-1) for the dummy variable method.
[21] Either one of the firms or the constant term has to be dropped in equation (2.5) to avoid perfect collinearity.

$$\hat{U}_i = \max(\hat{D}_i) - \hat{D}_i \qquad (2.7)$$

The mean deviation approach (commonly known as the within estimator procedure) replaces Y_{it} and X_{it} with $Y_{it} - \overline{Y}_i$ and $X_{it} - \overline{X}_i$ before applying OLS. This time the individual intercepts are recovered as the means of the residuals for each firm:

$$\alpha_i = \overline{Y}_i - \hat{\beta}\,\overline{X}_i \qquad (2.8)$$

where $\alpha_i = \beta_0 - U_i$.

Individual efficiency is found by assuming the largest intercept corresponds to 100 per cent efficiency (i.e., max α_i). Namely:

$$\hat{U}_i = \max(\hat{\alpha}_i) - \hat{\alpha}_i \qquad (2.9)$$

As an example consider the results obtained by Schmidt and Sickles (1984) for the American domestic airline industry. Continental is found to have the largest dummy variable (intercept) value (0.783). This airline then is assumed to be operating at 100 per cent efficiency (i.e., $U_i = 0$). Calculating the efficiency of another airline, say Western, is achieved by subtracting the dummy coefficient (or intercept value) for Western (0.763) from the value for Continental. The resulting value (0.02) shows how less efficient Western is compared to the best-performing airline (i.e., Western is operating 98 per cent efficiently).

The FE approach benefits from allowing inefficiency to be correlated with the other explanatory variables (although it still assumes there is no structural dependence between the inputs and the random error term). However, it is only really applicable when the dataset fully "exhausts" the population (i.e., when the sample is the population). Also, if there are variables which vary across firms but are invariant over time the FE method is intractable. Omitting these variables is ill-advised because this will bias the resulting efficiency scores. Allowing the inefficiency component to be a random sample from a larger population eliminates these problems. This method is commonly called the random effects (RE) model. The RE model can be estimated using GLS or ML. The GLS version when applied to stochastic production frontiers is formulated as:

$$Y_{it} = B_0 - \mu_i + X_{it}\beta + V_{it} - (U_i - \mu_i) \tag{2.10a}$$

If we let $B_0^* = B_0 - \mu_i$ and $U_i^* = U_i - \mu_i$ then equation (2.10a) becomes:

$$Y_{it} = B_0^* + X_{it}\beta + (V_{it} - U_i^*) \tag{2.10b}$$

Here $E(U_i) = \mu_i$ is positive and the terms in parentheses represent the error components. Alternatively, if U_i is iid $N(0, \sigma_U^2)$ and we let $\alpha_i = B_0 - U_i$, then:

$$Y_{it} = \alpha_i + X_{it}\beta + V_{it} \tag{2.11}$$

where α_i and V_{it} are the error components.

The benefit of the GLS procedure is that it weights observations inversely to their variances, whereas OLS assumes equal weights. As a result, GLS is used when the specification suffers from potential heteroskedasticity and/or autocorrelation. The weighting given to each observation is found in two-stages[22]. In the first stage, the residuals from OLS of the pooled sample (between estimator) and the within estimator provide (unbiased) estimates of the variance components (σ_V^2, σ_α^2)[23]. In the second stage, OLS is applied to the following transformations[24]:

$$Y_{it}^{*} = Y_{it} - \hat{\vartheta}\bar{Y}_i$$
$$X_{it}^{*} = X_{it} - \hat{\vartheta}\bar{X}_i \qquad (2.12)$$

where

$$\vartheta = 1 - \sqrt{\frac{\sigma_V^2}{\left(\sigma_V^2 + T\sigma_\alpha^2\right)}} \qquad (2.13)$$

FE and pooled OLS can be treated as special cases of equation (2.12) where ϑ = 1 and ϑ = 0, respectively. In terms of measuring individual efficiency, the residuals $\hat{\varepsilon}_{it} = Y_{it} - X_{it}\hat{\beta}$ from the transformed regression are averaged for each firm (Schmidt and Sickles, 1984):

$$\hat{\alpha}_i = \frac{1}{T}\sum \hat{\varepsilon}_{it} \qquad (2.14)$$

[22] This is the general case where the variances of the error components are unknown. As a result, the class of estimators is known as feasible GLS.
[23] The variance parameters become σ_V^2 and σ_U^2 if using equation (2.10b).
[24] See Judge *et al.* (1985).

As in the FE model, individual efficiency can then be calculated using equation (2.9).

If specific distributions of V_{it} and U_{it} are made - normal and half-normal (Pitt and Lee, 1981) or normal and truncated normal (Battese and Coelli, 1988) - ML estimation is possible. Individual efficiency can then be determined using the Jondrow *et al.* (1982) method or the generalisation proposed by Battese and Coelli (1988) in the same way as described in Section 2.3.2. Because of the imposition of specific assumptions for the efficiency term the ML approach is more restricted than GLS.

A third method of estimation is the Hausman-Taylor (H-T) estimator (Hausman and Taylor, 1981). Essentially H-T estimator is a hybrid of FE and RE, allowing efficiency to be correlated with some of the regressors whilst continuing to assume the estimates are random. In essence, this is an instrumental variable approach to estimating equation (2.10) or equation (2.11) and the procedure for obtaining individual efficiency is the same as that under feasible GLS. Park *et al.* (1998) provide a recent treatment.

FE, GLS and H-T only provide consistent estimates as N and T approach infinity. N needs to approach infinity because of the assumption made about the best-practice firm. A large T is required to consistently estimate the individual intercepts. GLS is justified when N is large compared to T, although if efficiency is correlated with the regressors the GLS estimates are biased and inconsistent (unless N and T approach infinity, in which case FE = RE). ML estimates are more efficient than FE, GLS and H-T provided the distributional assumptions are correct (or N approaches infinity) and efficiency is uncorrelated with the regressors.

Given the above, individual measures of efficiency will vary depending on the method chosen, although it may be the case that the estimates provide identical rankings when T is large (Schmidt and Sickles, 1984) and similar rankings for finite samples (Gong and Sickles, 1989). Hallam and Machado (1996) add that higher average efficiency is positively related to the number of distributional assumptions; average efficiency is greatest under ML (most restrictions) and lowest for the within estimator (least restrictions).

Time-Varying Efficiency

The assumption that efficiency is time-invariant is perhaps only applicable when there are a relatively small number of time-periods. As the number of time-periods increases it becomes more and more unreasonable to assume time-invariance. In other words, it becomes less reasonable to assume that firms do not learn from past experiences. Assuming efficiency is time-varying, equation (2.11) can be written:

$$Y_{it} = \alpha_{it} + X_{it}\beta + V_{it} \quad (2.15)$$

where

$$\alpha_{it} = B_0 - U_{it} \quad (2.16)$$

Unlike the time-invariant model, α and U now depend on both i and t. Cornwell *et al.* (1990) consider α_{it} as a parametric (deterministic) function of time and replace equation (2.16) with $\alpha_{it} = \omega_{i1} + \omega_{i2}\, t + \omega_{i3}\, t^2$, so that estimation of efficiency is based on a constant, time and a time-squared parameter. In addition, they consider this kind of specification for a model that varies in slopes as well as intercepts, although the empirical analysis is restricted to variations in the intercepts only. Lee and Schmidt (1993) offer a more flexible model where $\alpha_{it} = \omega_t \psi_i$. However, unlike Cornwell *et al.* where efficiency is allowed to vary across firms, this specification assumes the temporal pattern of efficiency is the same for all firms. Both of these models can be estimated under conditions of within, GLS and H-T and individual efficiency estimates are again provided by equation (2.9), albeit this time for each time-period[25].

Other forms of temporal variation are provided by Kumbhakar (1990) and Battese and Coelli (1992, hereafter BC(1992)). In each case the structure of the efficiency term follows an exponential function of time. The respective model specifications are:

$$U_{it} = \left[1 + \exp\left(bt + ct^2\right)\right]^{-1} U_i \qquad (2.17)$$

and

$$U_{it} = \exp\left[-\eta\left(t - T_i\right)\right] U_i \qquad (2.18)$$

Equation (2.17) involves the estimation of two unknown parameters (b, c). In equation (2.18) there is a single unknown parameter (η) which takes on a well-defined structure. Additionally, t is the time-period currently observed and T_i is the last period of the panel. Both models are estimated using ML methods so distributional assumptions regarding U_{it} and the independence of U_{it} from the input regressors need to be made. For example, in equation (2.18) U_{it} is assumed iid and distributed as truncated normal (half-normal is a

[25] Recall that previously these residuals were averaged (i.e. equation (2.14)).

special case). Finally, the temporal pattern in both models is assumed to be the same for all firms and time-invariance can be considered as a testable restriction.

Kumbhakar *et al.* (1997) compare efficiency levels using three of the above models (Cornwell *et al.*, Lee and Schmidt, and BC (1992)) on a sample of 15 Colombian cement plants observed over a 21 year period. Based on a priori information about the industry, they suggest using the BC (1992) time-varying model (i.e., equation (2.18)) largely because of its ability to accommodate technical change. In contrast, the models of Cornwell *et al.* and Lee and Schmidt are unable to separate technical change from efficiency change; instead both compute a total productivity measure (technical change plus change in technical efficiency). Notwithstanding the benefits of BC (1992), Kumbhakar *et al.* do add that the choice of model needs to be considered on a case-by-case basis.

The basic time-varying or time-invariant panel data models can be extended to include "unbalanced panels" (where firms are not observed over the entire sample period). The incompleteness in the panel can occur randomly or nonrandomly (known as a rotating panel). A random panel means that the total number of observations in each time-period can (and often do) vary. For a rotating panel, although the total number of cross-sectional units varies, the total number of observations in each time-period remains the same (every new observation added has to be matched by the removal of another). Seale (1990) offers a procedure for estimating unbalanced (random) panels and Heshmati *et al.* (1995) use a rotating unbalanced panel[26]. The econometric implications of unbalanced panels are discussed in Baltagi (1995). The only real complication that

[26] A third class of unbalanced panels exists: pseudo panels (see, Heshmati and Kumbhakar, 1997, for an application).

concerns us is that the weights for GLS estimation now depend on the number of observations for each firm.

2.4 Inefficiency Effects[27]: Models and Applications

Having obtained individual efficiency scores using the methods described above a number of studies have sought to explain the causes of efficiency. Frequently these determinants are modelled using a two-stage procedure (e.g., Hill and Kalirajan, 1993; Sheehan, 1997). In the first stage, efficiency is estimated following any of the methods outlined in Section 2.3. In the second-stage, the estimated individual efficiency scores form the dependent variable ($\hat{U}_{it}$) and are regressed on a set of "appropriate" exogenous variables ($Z_{it}\delta$):

$$\hat{U}_{it} = Z_{it}\delta + W_{it} \qquad (2.19)$$

where $W_{it} \sim N(0, \sigma_W^2)$.

There are a number of problems with this procedure. Firstly, the individual efficiency estimates are assumed to be independent and identically distributed (iid). However, in the second-stage the estimated efficiency is a function of a set of explanatory variables (efficiency effects), implying that the efficiency scores are not identically distributed. This kind of methodological problem occurs mainly in cross-sectional stochastic frontiers. It does not occur in panel data models as long the model is estimated using within, LSDV or GLS because recall that these estimators do not require distributional assumptions regarding the efficiency term.

A second problem, which applies equally to all model types, relates to the estimation procedure in the second-stage. The use of OLS in estimating the second-stage is not appropriate (the estimates are inefficient) because the dependent variable is one-sided[28]. Specifically, it is bounded between zero and one and, as such, the appropriate estimation procedure should account for the limited nature of the dependent variable. However, the use of limited dependent variable techniques, such as the tobit or probit, are impractical in parametric models because they require a significant number of observations to be performing optimally (100 per cent efficient). It is often the case that there are no firms (if efficiency is estimated using ML) or relatively few firms (as is the case in within, LSDV and GLS) performing optimally.

A method for dealing with the above problems has been suggested in papers by Kumbhakar *et al.* (1991) and Reifschneider and Stevenson (1991), with Battese and Coelli (1995, hereafter BC(1995)) providing an extension to panel data. Each of these papers suggests estimating the production function parameters (the X_{it} variables) and the inefficiency effects (Z_{it} variables) in a single-stage, so that the sources of inefficiency are built directly into the regression. Using ML as the estimation procedure, this means the limited distribution of inefficiency is directly incorporated into the likelihood function (see Chapter 6 for details). The model, based on BC (1995), takes the following form:

$$U_{it} = Z_{it}\partial + W_{it} \tag{2.20}$$

[27] We generally talk about inefficiency (rather than efficiency) effects in order to be consistent with the literature here.

This is equivalent to equation (2.19). W_{it} is a random variable which again is $N(0, \sigma_w^2)$, but this time is truncated from below ($W_{it} \geq -Z_{it}\partial$). Alternatively, and consistent with equation (2.20), U_{it} is a non-negative truncation (at zero) distributed as $N(Z_{it}\delta, \sigma_U^2)$. The model extends the truncated normal formulation discussed earlier by allowing the mean to vary across firms rather than assuming it to be constant for all firms. If equation (2.20) only includes an intercept term the specified model reduces to the truncated normal with constant mean. If the intercept term is also zero the model reduces to a half-normal specification.

The basic model has been extended to include interaction terms between the production frontier inputs and the inefficiency effects (Huang and Liu, 1994). The benefit of using this approach occurs if it is likely that the inefficiency effects are greater for some inputs than others. This means that the shift in the production frontier for different firms depends on the level of the production inputs. For example, firms may have more knowledge and expertise in using certain inputs in certain processes than using all inputs in different processes or the same process using different inputs. The extent to which these interactions affect inefficiency establishes the degree of non-neutrality exhibited by the production frontier.

Recently there have been an increasing number of empirical applications of the single-stage estimation procedure. Agriculture has been the main focus of attention: Nigerian croppers (Ajibefun *et al.*, 1996); Pakistan production of wheat (Battese *et al.*, 1996) and cotton (Battese and Hassan, 1998); and UK potato production (Wilson *et al.*,

[28] In addition, the standard errors of the estimated dependent variable also need to be adjusted (Topel and Murphy, 1985).

1998). Also, there have been studies in Swedish banking (Battese *et al.*, 1998), Kenyan manufacturing (Lundvall and Battese, 1998) and Australian coal-fired power plants (Coelli, 1996b).

The choice of agriculture over other industrial sectors seems to be motivated by the availability of data. The single-stage specification requires data on the determinants of inefficiency in addition to accurate measurement of the production frontier inputs. For example, Wilson *et al.* (1998) regress man hours of labour, the degree of mechanisation, the application of fertilisers and land size on the amount of potatoes harvested to estimate the production frontier. The inefficiency effects are thought to arise due to farm specific characteristics (i.e., how the crops are rotated, level of irrigation and storage and the size of the farm holding) and managerial ability (years of experience). In the other studies listed in the preceding paragraph, managerial ability has been measured by age, formal schooling and level of farm-specific experience. However, these measures seem to be introduced on an ad hoc basis rather than through any formal theoretical model.

The advantage of being able to derive estimates of efficiency in this way is that it enables us to link performance to both firm and managerial characteristics. However, this means that the derivation of the efficiency term takes on an added significance: an accurate measure of efficiency is essential in order to derive meaningful conclusions about the determinants of efficiency. The important methodological issue here is whether the inputs are measured correctly and all "useful" inputs have been accounted for in the production frontier. If there is measurement error or missing inputs, the efficiency measures will be misleading[29].

Even if all inputs can be accounted for and measured without error, the model needs to be correctly specified. The most popular functional form has been the Cobb-Douglas (C-D) specification. The linear form is:

$$\ln Y_{it} = \beta_0 + \sum_{i=1}^{n} \beta_j (\ln X_{jit}) + V_{it} - U_{it} \tag{2.21}$$

The appeal of the C-D specification is that it only requires a calculation of the logarithms of the output and the inputs. However, the function assumes an elasticity of substitution equal to unity for all inputs and the firm's technology is characterised by constant production elasticities. A more flexible function that does not impose these restrictions is the transcendental logarithmic (translog) production function:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j (\ln X_{jit}) + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} \beta_{jk} (\ln X_{jit})(\ln X_{kit}) + V_{it} - U_{it} \tag{2.22}$$

Equation (2.21) can be considered as a restricted version of equation (2.22), i.e. when $\beta_{jk} = 0$. Often, much simpler forms of equation (2.22) are analysed because of multicollinearity and degrees of freedom problems.

Overall, previous attempts at measuring the determinants of efficiency have been disappointing. To quote one study:

> We suspect that, in many empirical analyses using stochastic frontier models, differences across firms in efficiency levels are statistically insignificant, and much of what has been carefully explained by empirical analysts may be nothing more than sampling error (Horrace and Schmidt, 1996, p. 281).

[29] Some would argue that the random term should account for both of these occurrences.

The basic problem is a lack of confidence in the efficiency scores obtained. This arises because in many cases the inputs are unmeasurable (usually due to problems of disclosure), or are measured with error, or there is functional form mis-specification. As a result the efficiency levels will be contaminated and the explained efficiency cannot be attributed to any one source.

2.5 Sporting Production Functions and Production Frontiers

The idea of a production function in team sports[30] is straightforward. The product (the individual match) is produced by two teams who employ playing and managerial resources. This production process is the same for all teams in the industry and essentially remains the same over time. The defining feature which distinguishes sport from other industries is that it is not possible to produce the product without the assistance of a rival (i.e., other teams). In this respect sport industries are unique in that they require competition on the field and cooperation off it[31]. The reason for this is clear. If teams competed for consumers (fans and spectators) off the field then in the short-run the more successful teams would earn higher revenues (through increased ticket and merchandise sales) and attract the best players. Over time, however, these revenues would not be sustained because less successful teams, who earn less money and lose their best players to the more successful teams, will find it even more difficult to compete on the playing field. In the long-run consumers will lose interest in the product because the outcome of the game has become predictable. Put simply, consumers want to watch games between more rather than less equally matched competitors. Neale

[30] The focus here is on team sports (i.e. association football, rugby, baseball, basketball, and American football) rather than individual sports such as golf and tennis.

(1964) famously calls this the Louis-Schmelling paradox – a champion requires a strong challenger.

To achieve cooperation teams are organised into leagues. The sporting league, acting as cartel coordinator, determines the necessary guidelines (such as the distribution of revenue and the mobility of players) in order to curtail the amount of competition that takes place between teams, safeguard the competitive balance and thereby maximise joint (industry) profits. The notion that uncertainty of outcome matters has been investigated in numerous demand studies both in the UK and in North America. A number of other studies have focussed on the mechanisms with which competitive balance can be improved either through labour market restrictions or cross-subsidisation policies (see, Fort and Quirk, 1995, for a review).

Because of the constraints imposed by the league it becomes vitally important that the individual teams are maximising their performance from a given level of resources. Usually the goal of the individual team is to win as many matches as possible. However, the objective of maximising the number of wins is somewhat controversial. Much of the American literature (Scully, 1995; Fort and Quirk, 1995) proposes profit (wealth) maximising behaviour on the part of the clubs because of the considerable profitability of individual teams in American sports[32]. For example, Scully (1995) finds only 11 per cent of clubs from the four dominant American team sports (baseball, basketball, American football and ice hockey) reporting gross operating losses for the 1990 and 1991 seasons. A very different story prevails in English professional football: only 38 per cent of the 92 clubs report an operating profit for the financial year 1997.

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[31] Mutual interdependence also features in agriculture through worker and producer co-operatives.
[32] Vrooman (1997) argues that American sports teams are also run by 'sportsman-owners' so that profit maximisation is tempered by the desire to win as well.

This situation has prevailed for a long time and explains why economists model the behaviour of football clubs within a utility maximising framework (Sloane, 1971). Still, evidence suggests that there is a high correlation between team playing success and club profitability (Scully, 1995) so the appropriate objective, at least in terms of a production function, may well be a mute point (see Chapter 3 for more details on this).

Rottenberg (1956) first articulated the idea of a sporting production function:

> The product is the game, weighted by the revenues derived from its play. With game admission prices given, the product is the game, weighted by the number of paying customers who attend. When 30,000 attend, the output is twice as large as when 15,000 attend.... A... team, like any other firm, produces its product by combining factors of production.... the players of one team [are] the factors and all others (management, transportation, ballparks, and the players of the other team), another (p. 255).

Attendance seems to be a slightly obscure way of measuring output. These days attendance is invariably used as the dependent variable in demand studies. The "confusion" over using attendance as an output measure has probably been because consumption and production occur simultaneously. Furthermore, if players and management are to be considered as factors of production then the ouput measure should in some sense relate to their performances (the result of the match).

The use of team performance as an output measure was first proposed by Scully (1974) in his study of American baseball. He modelled output (percentage of matches won) as a function of player and non-player (e.g. management, capital and team spirit) inputs. Subsequently, almost all studies of sporting production functions have measured output in terms of team performance. For example, Zech (1981) identifies four categories of skill which should be included in a baseball production function: hitting, running, defence, and pitching. Similar categories have been used for production functions in basketball (Scott *et al.*, 1985) and American football (Atkinson *et al.*, 1988). Schofield (1988) estimates a production function for English county cricket and Carmichael and Thomas (1995) apply a production function to English rugby league. These two studies endogenise player performance so that the production function is determined through a system of recursive equations. However, empirically both studies estimate a single-equation model treating the player inputs as exogenous in the same way as the American studies. The only UK study to date on English football is provided by Szymanski and Smith (1997).

All of the above studies estimate production in the traditional sense. That is, each one estimates an average production function. Furthermore, these studies do not adequately consider the contribution of the manager. At best, most enter one or two variables on the right-hand side of the regression. For example, Carmichael and Thomas (1995) use a managerial variable based on years of coaching experience which is only significant (at the 5 per cent level) in one of the 12 models considered. Zech (1981) uses two measures - years managed in Major League baseball and the manager's lifetime win-loss ratio. Neither of them is significant.

Undoubtedly, managerial performance is very difficult to measure. One way of addressing this is to measure the contribution of the manager separately from the contribution of the players. This can be achieved by estimating a production frontier. Surprisingly, very few sports studies use this technique, and those that do use data from American sports. The first study to apply production frontier analysis was Zak *et al.* (1979). They analysed cross-sectional data from the National Basketball Association (NBA) for the season 1976/77. Using a deterministic approach and the match as the unit of observation, their main finding is that efficiency for each of the teams approximates 100 per cent (the lowest efficiency rating being 0.997, i.e., 99.7 per cent). This result is surprising because, as mentioned earlier, with a deterministic model the entire deviation from optimality is the result of inefficiency.

More recently, Hofler and Payne (1997) compare the results of Zak *et al.* with an approach using a stochastic frontier for the 1992/93 NBA season. However, unlike Zak *et al.* the dependent variable is the team's seasonal winning percentage. Average efficiency is much lower (89 per cent), so accounting for randomness reduces efficiency. But we need to note two things. Firstly, Zak *et al.* only analyses the efficiency of five (Atlantic Division) teams. This may not be a representative sample. Secondly, there is a difference of nearly 20 years in the sample periods. Many changes could, and indeed have, occurred at both the institutional level and the individual level. For example, both free agency and salary restrictions (e.g., salary cap) were introduced to basketball in 1983.

Hofler and Payne (1996) also applied stochastic frontier analysis to the National Football League (NFL). Using panel data (N = 28 and T = 5), the results are similar to their cross-sectional study for basketball; the overall mean efficiency for the five years is 96 per cent, with the lowest individual efficiency being 81 per cent. Interestingly, mean efficiency falls throughout the period, although not greatly. This is due to the nature of the specified model rather than falling team standards[33], although the statistical properties of the model suggest that none of these efficiency scores are different from 100 per cent.

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[33] This is because equation (2.17) is the specified model. The model is constructed in such a way that efficiency can only consistently rise, fall or stay the same (see Section 2.3).

None of these studies attempt to explain the efficiency levels. Given that the production frontier inputs in these studies are all aspects of player quality, an interesting question to ask is do the efficiency scores measure a manager contribution and, if so, what factors influence managerial efficiency?

Porter and Scully (1982) use a deterministic parametric approach and two playing inputs - team slugging percent (hitting measure) and team strike out to walk ratio (pitching measure) - to estimate a baseball production frontier. Although not extensive, they find a positive correlation between managerial efficiency and tenure, and managerial contribution, in terms of team output, is comparable with the output of individual (superstar) players.

Scully (1994, 1995) compares efficiency levels in baseball, basketball and American football. The input measure adopted by Scully is team scoring relative to opponent scoring. Such a measure is clearly inappropriate as it is likely to include both the contribution of the players *and* the manager. Nonetheless, Scully finds that efficiency levels in all three sports improve over time (contrast this with the findings of Hofler and Payne, 1996, above) with mean efficiency being highest in baseball and lowest in American football. One reason for the variation in efficiency between the sports could be the greater demands placed on managers in sports where team strategies are important (see Chapter 3 for details).

Ruggiero, *et al.* (1996) compare the results of a deterministic frontier with a stochastic frontier for Major League baseball. They adopt a Cobb-Douglas specification[34] and a number of player input measures are used: slugging percent, batting average, stolen bases, fielding percent, and earned run average. Their data set covers the period 1982-1993 and they find both models produce almost identical efficiency rankings. They favour the stochastic version because random influences are considered. In contrast, Scully (1994), although coming to similar conclusions, favours the use of a deterministic equation. The similarities in the results under the stochastic and deterministic approaches are not surprising given the accuracy with which the inputs are measured and may well suggest that random factors only play a minor role in sporting production functions and production frontiers that use seasonal data.

In each of the studies considered, the contribution of the manager depends on the way the inputs are measured. It has been suggested that managers of professional sports teams influence team performance in two ways. First of all they turn actual performance into wins. This is known as the direct effect and involves the strategic side of management: how the playing inputs are used during the production process. Second, managers are likely to affect team performance through training and motivation (i.e., leadership). This is the indirect effect and measures the extent to which the manager enhances a player's current performance relative to the player's historical (career) performance[35].

The primary focus in all the studies considered so far has been the direct effect of the manager. Each of the above studies measures player performance at the end of the season under review. In those studies that use team scoring relative to opponent scoring (Scully, 1995; Horowitz, 1994) the direct effect can be interpreted as turning team

[34] This is the preferred specification in the majority of sport studies.
[35] These roles are discussed in more detail in Chapters 3 and 4.

scoring into team victories. Estimating a production frontier using these measures is ill-advised because input measures are little more than proxies for the output measure (Ruggiero *et al.*, 1997). In the remaining studies (Hofler and Payne, 1996,1997; Porter and Scully; Zak *et al.*), which use measurable aspects of player performance, the ability to turn these aspects into team scoring (conceding) is included as an additional strategic factor[36].

There are two ways of estimating the indirect effect of the manager. Singell (1993) and Kahn (1993) analyse the direct and indirect effects separately. The direct effect is measured using conventional production function specifications; Kahn uses a predicted salary model as a proxy for managerial performance, while Singell uses managerial experience measures in a grouped data probit model. In both studies, the indirect effect is then analysed using separate regressions based on individual player performance in the season in question relative to the historical performance of the particular player. Kahn looks at the effect of a new manager on player performance and Singell observes the performance of players after they have moved to a new club.

Although both studies report significant managerial coefficients in these specifications, it is questionable whether the improvement is due to the manager. Performance is more likely to improve in the first season, particularly in the case of player movements, because players and managers want to "prove" themselves to their new employers. One solution to this problem is to estimate the indirect effect and the direct effect together. This involves using ex ante player performance information (i.e.,

[36] Another way of analysing the direct (strategic) effect has been discussed by Clement and McCormick (1989). They measure managerial performance in terms of team line-up decisions (better managers make better decisions regarding the assignment of playing time). The coefficient of determination from a regression of minutes played per season as a function of measurable player performance variables measures managerial performance.

player performance measured at the start of the season), with output continuing to be measured at the end of the season. Fizel and D'itri (1996) provide an application of measuring both the direct and indirect effects using a deterministic frontier for college basketball. In contrast to the results discussed above, mean efficiency is substantially lower.

2.6 Summary

In this chapter we have outlined the way in which stochastic frontier analysis can be used to generate efficiency scores of firms and individuals. Although a number of studies have compared alternative estimation procedures (COLS versus ML; FE versus RE, H-T and ML) and different functional forms (C-D versus translog), no study has tested the sensitivity of the efficiency levels under alternative output and input measures. This may, in part, be due to data limitations as well as a lack of confidence in the reported efficiency levels. In addition, previous studies, sport or otherwise, have paid sufficient attention to the determinants of efficiency. In particular, the question of single or two-stage specification has only recently been addressed.

The sports industry provides a perfect laboratory for addressing each of these problems because data are widely available with which to measure both input and output. Moreover, these data are measured more accurately than in other industrial sectors. Most of the American literature in this area favours the deterministic approach over the stochastic approach. Neither approach has been used successfully to analyse the determinants of efficiency.

No study, as yet, has used production frontier techniques in UK team sports. One of the major obstacles to the estimation of sporting production functions for English football is the lack of detailed statistics on player performance akin to those available for American sports. In contrast, financial expenditure on players (transfer values and wages) is more readily available. These financial expenditure measures therefore form the basis with which we measure playing talent.

This thesis builds on previous research into production frontiers in three ways. Firstly, the manager is the unit of observation so the efficiency level represents an objective measure of managerial performance. Most previous studies have analysed firm (club) efficiency. Secondly, efficiency is estimated under various model specifications. As in other studies, we examine alternative estimation procedures. But one aspect that has not been considered until now is the effect alternative input and output measures have on efficiency scores. Compared with other sectors, in team sports data availability enables us to analyse the sensitivity of the efficiency scores to alternative input and output measures. Thirdly, once we have chosen the appropriate specification we then formally model the determinants of managerial efficiency using the kind of human capital and agency (incentive) factors discussed in Chapter 1.

Moreover, this is the first study to examine the link between team performance and managerial efficiency for any industry in the UK economy. We believe the results will provide valuable evidence with which policy-makers can make rational and informed decisions about managerial appointment and retention not only in the football industry but also in the corporate sector as a whole. In the next chapter we provide an overview of the UK football industry.

CHAPTER 3

ENGLISH PROFESSIONAL FOOTBALL: CLUBS, PLAYERS AND MANAGERS

3.1 Introduction

The sport sector is one of the most important industries in the UK. A survey by the Sports Council (1992) found that in 1990 the sport-sector generated £8.27 billion in "sport-related activity" (equivalent to 1.7 per cent of gross national product) and a further £9.75 billion in consumer expenditure.

Since 1990, one sport in particular has contributed a major part of the total income generated by the sport sector: the English professional football industry. The football industry is currently experiencing unprecedented prosperity; figures for the 1997/98 football season reveal that the 92 professional football clubs generated a combined income of £829.4 million (Deloitte and Touche, 1999). Five years earlier the corresponding figure was £322.2 million (Touche Ross, 1994). The financial performance of the football industry has a major bearing on jobs in the leisurewear, construction and media industries, and the growing number of universities offering courses on the economics, business and finance of football also highlight the widening appeal and growing importance of the football industry.

Now as never before the football industry is operating like a business. In 1997 a BBC Panorama programme vividly portrayed the 'beautiful game' as the 'money game'. A succession of clubs have raised capital through listings on the Stock Exchange and the Alternative Investment Market replacing the more traditional methods of bank financing and donations. As a consequence clubs now employ commercial managers and financial advisors as well as football players and managers. The money flowing into football has enabled the larger clubs to develop modern, all-seater stadia equipped with corporate hospitality and executive boxes. These developments, together with merchandising and increased media exposure, have continued to strengthen the brand allegiances of individual clubs. Players have benefited too, becoming highly prized assets with the top players commanding weekly salaries that exceed the annual average wage for all industrial sectors.

The business orientation of football is reflected in the recent publication of two books on the industry: *Winners and Losers: The Business Strategy of Football* (Szymanski and Kuypers, 1999) and *The New Business of Football* (Morrow, 1999). Nowadays football is just as likely to appear on the financial pages as the back pages of newspapers and the increasing interest in the football sector has led to a huge array of publications ranging from financial issues (*Soccer Investor* and *Soccer Analyst*) to player autobiographies.

Although the industry continues to prosper there is a growing polarisation between the top clubs and the smaller clubs. Over two-thirds (£569 million[1]) of football's income is generated in the top division (the Premier League). Financially, the Premier League is the most prosperous in Europe (exceeding the turnover of the top divisions in Italy, Spain and France) and one club, Manchester United, is considered by many to be the richest club in the World. Based on figures available for the 1997/98 season, Manchester United's turnover alone exceeds the combined turnover of all clubs operating in Divisions 2 and 3.

Wage inflation has also spiralled in recent years. For some clubs the wages bill exceeds annual income. This is clearly not sustainable in the long-term. Finally, and of particular concern here, the pressures on clubs to succeed continues to result in high rates of managerial turnover well above that in the corporate sector. In contrast to football's more recent problems, high managerial turnover is a long-standing characteristic of football.

The renaissance in the football industry is a recent phenomenon and can be traced back to the start of the 1990s. Football's circumstances were very different during the period between 1970 and the mid-1980s. During this period the popularity of football was in decline. Attendance in the top division fell from an average of 31,352 in the 1971/72 season to an average of 19,300 by the end of the 1987/88 season. Many reasons have been put forward to explain the trend, among the most common being: the economic climate of high unemployment and high prices, the rise of hooliganism from the late 1960s onwards (culminating in the Heysel disaster of 1985), and the increasing popularity of individual-based participation sports such as golf, tennis and swimming.

By the mid-1980s football appeared to be in permanent decline, its fortunes mirroring many of the social problems (e.g., de-industrialisation and rising crime) being experienced by society in this period. On the footballing side, the international team

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[1] Deloitte and Touche (1999).

failed to live up to expectations and the stadiums of many domestic clubs were decrepit and dangerous. In short, football needed to re-invent itself and the media – television in particular - was to play a pivotal role in this process. The arrival of British Satellite Broadcasting (BSB) in 1988 contributed towards the collapse of the BBC/ITV cartel which had effectively operated as the sole purchaser of televised football rights. This led to a competitive round of negotiations, before ITV secured an exclusive four-year contract at substantially increased fees. Crucial to the speed with which these changes occurred were the events which took place at Hillsborough in 1989 when 96 Liverpool fans were crushed to death on the terraces during an FA Cup semi-final. The following year, the Taylor Report (Taylor, 1990) recommended that football grounds should be made all-seater as a necessary way forward in eliminating the problems of crowd misbehaviour and achieving a safer environment for the football spectator.

By 1992 many of the top division clubs had secured grants (in part from the Football Trust) to carry out the necessary improvements and were well on the way to providing all-seater stadia. However, many of the big clubs were becoming increasingly dissatisfied with the League's revenue sharing arrangements, and the owners wanted some kind of return on the investments they had undertaken - the Taylor Report had stipulated that the financing of stadium development should not be passed on to the fans by way of higher admission prices. One way to generate extra revenue was to alter the distribution of television revenue. Prior to 1986 all television revenue was shared equally among the 92 clubs in the Football League. In response to a threatened breakaway by the leading clubs, the 1986 television deal altered the distribution such that clubs in Division 1 would receive 50 per cent of the funds, Division 2 clubs would receive 25 per cent, with the remaining 25 per cent being shared equally between clubs in Divisions 3 and 4. This arrangement remained in place during ITV's four-year contract. A potential breakaway was again on the agenda in 1991 when the FA published its *Blueprint for the Future of Football*, outlining the need for a Premier League comprising clubs in the old Division 1 with separate revenue creating potential. By this time BSB had merged with another satellite service, Sky, to become BSkyB[2]. The merger intensified the competitive bidding during negotiations for the rights to broadcast the newly established FA Premier League. BSkyB won the contract in 1992, securing a deal worth £304 million over five years[3].

Although academic interest in football continues to increase in the UK, economists have primarily been concerned with the determinants of demand (Dobson and Goddard, 1995; Baimbridge *et al.*, 1996) and the operation of the player transfer market (Carmichael and Thomas, 1993; Dobson and Gerrard, 2000)[4]. Much less attention has been given to the economic behaviour of football clubs (see, Sloane, 1971). Within a general team performance - club profit framework, Dobson and Gerrard and Szymanski and Smith (1997) consider the idea of a football production function, but neither separates the impact of the manager from the players in the production process.

The remainder of this chapter analyses the organisational structure and institutional characteristics of football in terms of both the overall industry and the individual clubs. Specific consideration is given to an examination of the ownership structure and control of football clubs and an analysis of the markets in which the services for football players and football managers are exchanged.

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[2] Effectively this was a take-over of BSB by Sky.
[3] For an interesting, if somewhat obstinate, account of the negotiations see Fynn and Guest (1994).

3.2 Organisational Structure: Industry Level

As mentioned in Chapter 2, the nature of the product in professional team (club)[5] sports is unique[6]; teams must co-operate to produce the product (the match). Although individual clubs wish to maximise the number of games won[7], the joint profits of the industry are maximised if teams are evenly matched (this assumes, however, that all the clubs are of a similar size). As noted in Chapter 2, the much-heralded terms of competitive balance and uncertainty of outcome have been extensively investigated both in the UK and North America. Let us re-clarify their meaning.

The idea is that the aggregate demand (usually measured by match attendance) for the product will be higher if there is a high degree of on-field competition, or uncertainty of outcome, than if there is domination by one or a few teams. For example, another factor that could explain the decline in football attendance from the late 1970s to the mid-1980s was the domestic dominance of Liverpool. In this period the club won the Division 1 championship in three consecutive years (1981/82, 1982/83 and 1983/84), the Football League Cup four years running (1981-1984) and the European Cup four times.

To achieve (or maintain) competitive balance clubs are organised within a league structure. In football at present there are two leagues: the Premier League which contains one division, and the Football League (which contains three divisions). The authorities of these leagues impose rules and restrictions to promote on-field

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[4] A wide array of articles and other publications can also be found in the areas of sociology, psychology, physiology and statistics.
[5] For the time-being the terms team and club will be used interchangeably.
[6] Rather facetiously, Neale (1964) refers to the sports industry as having "peculiar" economics.

competition. The authorities may introduce limitations on player movements (see Section 3.4.1) or the pooling of revenues in order to achieve a more equal distribution of resources. Given the relationship between the league and the clubs, Neale (1964) argues that the league should be considered as the firm and the individual clubs sub-units within the firm. Challenging such notions with specific reference to football, Sloane (1971) argues that this overstates the mutual interdependence of clubs. We are in agreement with this view. Individual clubs are separately owned and although they face some constraints from the governing authorities they are free to make their own decisions in terms of pricing policies, capital structure and team resources. Rather than a 'natural' monopolist, the industry is considered to operate as a 'natural' cartel - each firm is a separate entity but all firms find it mutually advantageous to co-operate.

The earliest example of a sporting league is in American baseball with the formation of the National League in 1876. In English[8] football the Football League was established in 1888 with an original membership of 12 clubs. Since then the League has undergone several phases of expansion and change. In 1892/93 a second division was introduced as a result of amalgamating with a rival competition, the Football Alliance. By 1921/22 two more divisions had been integrated; the first division of the Southern League became Division 3 (south), and the following year, Division 3 (north) was created from local leagues in Lancashire, the Midlands and the North East. In 1958 these two regional leagues were reorganised into nation-wide divisions: the new Division 3 contained the top half of each regional division, while the bottom half of each regional division formed Division 4.

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[7] Maximisation of profits is an alternative although not necessarily conflicting objective. This is because team wins and club profits are highly correlated (e.g., Scully 1995).
[8] Two Welsh clubs - Cardiff and Swansea - also play in the English league. Other clubs in Wales and clubs in Scotland have their own leagues.

The divisions are not autonomous. Promotion (clubs moving up a division) and relegation (clubs moving down a division) was initially on a "two-up" and "two-down" basis for Divisions 1 and 2, and "four-up" and "four-down" for Divisions 3 and 4. But from 1973/74 "three-up" and "three down" became the standard for Divisions 1, 2 and 3. Four clubs continue to get relegated from Division 3 and four promoted from Division 4[9]. The season 1986/87 saw two further changes. Firstly, the bottom club in Division 4 was to be replaced by the champions of the GM Vauxhall Conference[10]. Secondly, play-offs, contested between clubs finishing in positions three to six, were introduced to decide on the final promotional place in Divisions 2, 3 and 4. These changes were designed to increase interdivisional mobility.

The last and most significant change took place before the start of the 1992/93 season when the top twenty-two[11] clubs playing in Division 1 of the Football League broke away to form the FA Premier League. The remaining 70 clubs continue to operate under the Football League, and the old Divisions 2, 3 and 4 were renamed Divisions 1, 2 and 3. Although now a separate league, the Premier League continues to operate with the Football League structure: each season three clubs are relegated from the Premier League and three clubs are promoted (two automatically and one via the play-offs).

As a separate organisation, the Premier League allows the top clubs to retain all of the revenue raised from broadcasters and sponsors. For example, the 1996 agreement

[9] There have been exceptions to this rule. Only two clubs were promoted to Division 1 at the end of season 1986/87 (three clubs relegated). The following year, four clubs were relegated (three promoted). This was designed to reduce the size of the top division to 20 clubs (previously 22) and increase the size of Division 4 to 24 clubs (previously 22). This was subsequently reversed at the start of the 1991/92 season.
[10] Formed in 1979/80 as the Alliance Premier, and now known as the Conference League, this league operates on a semi-professional basis, bringing together major non-league clubs from regional leagues. Previously, the bottom four clubs of Division 4 had to apply for re-election.
[11] Twenty-two clubs in the Premier League for seasons 1992/93 and 1993/94, 20 thereafter.

with BSkyB for live football (and the BBC for edited highlights) is worth £743 million to the end of the season 2000/01. Specifically, the distribution of television income is based on performance rather than historical status. Under the BSkyB arrangement, 50 per cent of the income is shared equally amongst the Premier League clubs, 25 per cent is paid as merit payments according to final league placing, and 25 per cent is distributed as facility fees split equally between the clubs whose matches are broadcast. In the 1996/97 season, Manchester United (Premier League winners) received £6.3 million compared to the £2.8 million received by Nottingham Forest who finished in twentieth place (Morrow, 1999).

Previous television deals, when all four divisions came under the authority of the Football League, were modest by today's standards but more egalitarian because each of the 92 clubs received an equal share[12]. The formation of the Premier League and the separate negotiation of TV deals and sponsorship has resulted in a widening income gap between the big clubs at the prosperous end of the industry and the smaller clubs which remain in the Football League. Table 3.1 highlights the trend over the last five years.

[12] Live televised football in the UK commenced in 1983. The initial contract agreed between the BBC and ITV networks was worth £2.6 million per year for two seasons. Since then the figure has increased

Table 3.1 Turnover and Profitability in English Professional Football, 1992/93 to 1996/97 (£,000)

Season	Premier League		Football League					
			Division 1		Division 2		Division 3	
	R	π	R	π	R	π	R	π
1992/93	201,601	32,146	70,424	(8,346)	35,800	(1,117)	14,380	(1,022)
1993/94	241,479	40,831	95,759	(9,979)	29,865	(4,001)	19,905	(2,309)
1994/95	322,858	49,278	83,384	(16,158)	41,565	(3,650)	20,564	(2,702)
1995/96	346,224	51,916	103,902	(28,395)	41,734	(7,975)	25,382	(5,778)
1996/97	463,949	86,325	131,305	(12,263)	55,237	(9,157)	25,219	(6,565)

Sources: Deloitte and Touche (1996, 1997, 1998) and Touche Ross (1994, 1995).
Notes: R = turnover; π = operating profit (loss).

The contrasts offered by Table 3.1 are startling. Whereas turnover in the Premier League has doubled in the last five years (and operating profits have nearly trebled), clubs in the Football League struggle to break-even. During the 1996/97 season the Premier League created 67 per cent of total income generated. The 'average' Premier League club had an operating profit of £4.3 million compared to a deficit of £0.5 million for the 'average' club in Division 1[13]. The gulf between the lower divisions also seems to be widening. The desire of Division 1 clubs to achieve Premier League status is reflected in the high costs (low profits) compared to turnover. In contrast, the *raison d'être* for the majority of clubs in Divisions 2 and 3 continues to be survival[14]; the 'average' Division 2 and Division 3 club loses somewhere in the region of £300,000 to £400,000 each season[15]. The growing inequalities and the financial plight of many of the smaller,

exponentially: the annual rights fee increased to £3.1 million in 1986; the exclusive rights gained by ITV in 1988 cost £11 million before BSkyB quadrupled the fee to £42.8 million per season in 1992.

[13] This dramatic increase - compared to £2.6 million for 1995/96 season - can be partially explained by the £50 million advance from the BSkyB deal. In truth, these figures are somewhat misleading because although most Premier League clubs make an operating profit, almost all – with the exceptions of Manchester United, Blackburn, Liverpool, Newcastle, Sunderland and Tottenham – made a net profit (i.e., after transfer expenditure has been added or deducted).

[14] The fortunes of some of these clubs have improved through the injection of cash by wealthy benefactors (e.g., Mohamed Al Fayed at Fulham and Dave Whelan at Wigan).

[15] The financial position of some of the smaller clubs is improved through transfer income. However, the effect of the Bosman ruling, discussed in Section 3.4.1, is likely to reduce the positive impact of transfers on club profitability.

less wealthy clubs has led to proposals for restructuring Division 3 and the Conference League into two regional divisions to reduce the costs of travel and the additional attraction of derby matches (Deloitte and Touche, 1998).

Revenue is generated through three main sources: ticket sales (gate receipts and season ticket sales), broadcasting and commercial activity. Although historically ticket sales have contributed the highest proportion, there has recently been a shift towards the income-generating potential of broadcasting and commercial activities. The direct effect of television as a revenue source is likely to become increasingly important in the future with the technological advances of digital television leading the way to pay-per-view television. One study predicts that pay-per-view could be worth as much as £2.5 billion (Shurmer, 1997). However, the indirect effect of media coverage on commercial activity is also huge. Sponsorship is carried by league competitions (Carling, part of Bass Breweries, are the current sponsors the Premier League and the Nationwide Building Society are the current sponsors the Football League) and individual clubs in the form of shirt sponsorship (e.g., Arsenal are sponsored by Sega and Leeds are sponsored by Packard Bell). Sponsors also use advertising hoardings around the clubs' grounds and in some cases (e.g., Bolton and Huddersfield) the grounds themselves.

Merchandising in the form of sales of replica kits also contributes to the increasing amounts of cash flowing into clubs. Many of the major sportswear manufacturers (Nike, Adidas and Umbro) have invested substantial sums of money in clubs to supply their kit (e.g., Umbro currently pay Manchester United £7 million per year). Customers (fans and spectators) also spend money on anything from the traditional club hat and scarf to club endorsed milk, wine and tomato sauce.

Increasingly, football club stores are found in the high street and on the Internet. As one source suggests:

> Before long the loyal identikit [Manchester] United fan may have their mortgage through Old Trafford financial services, watch all the Reds' games on pay-TV on the net, own shares in David Beckham plc and take the kids on holiday to the Far East to watch the first team's merchandise-boosting summer tour (Observer, 23 May 1999, p. 23).

A major explanation for the vast amounts of money that is being paid by sponsors and customers is the club's name. Clubs have a readily identifiable brand name, and the strength of the brand name is associated with customer loyalty. Customers of (say) Everton could not be persuaded to regularly watch and purchase Liverpool related products no matter how badly Everton perform on the football field. Individual clubs know they have fan loyalty and this is being ever-increasingly exploited.

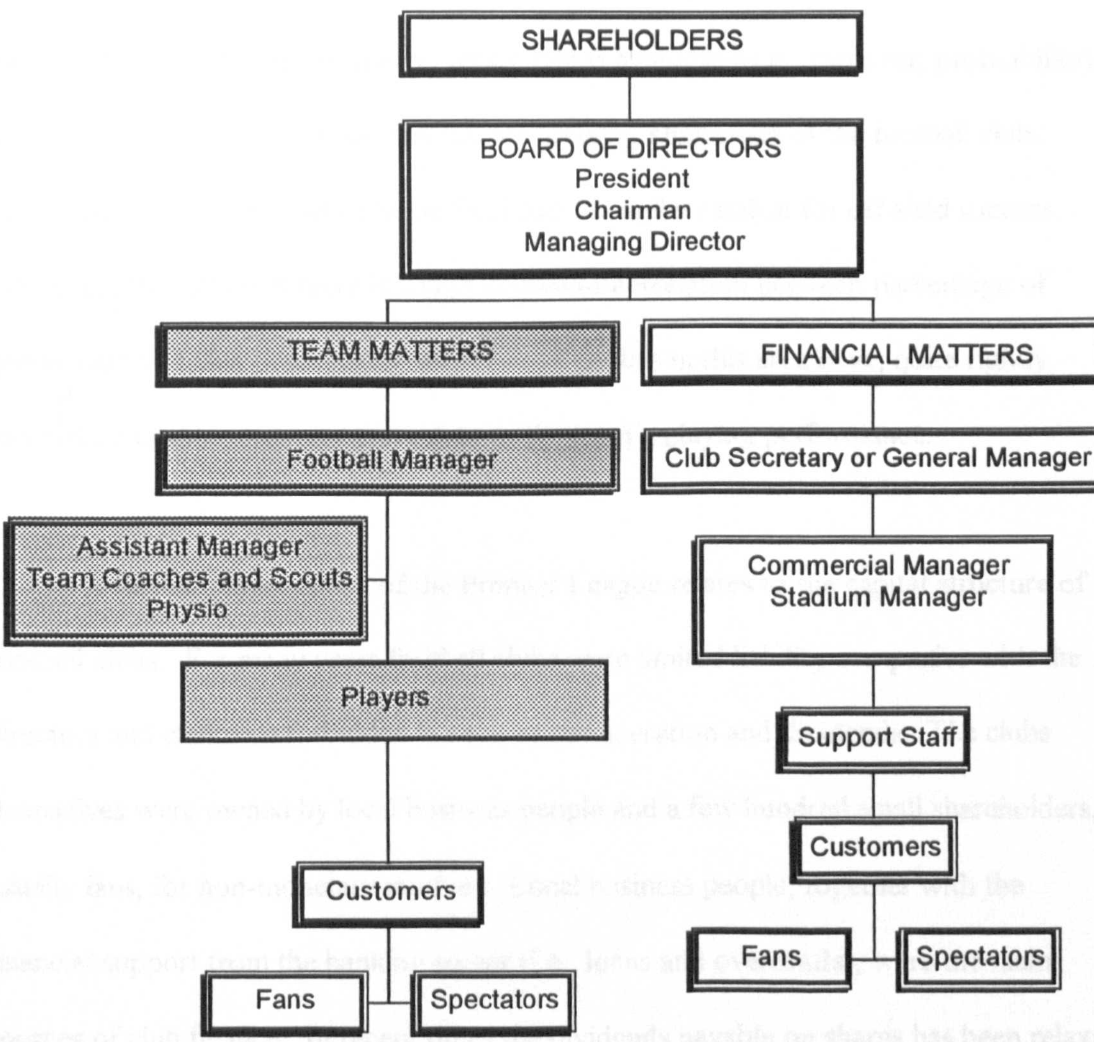
3.3 Organisational Structure: Club Level

As with any other type of firm, a football club involves relationships between owners, management, employees and customers. Figure 3.1 illustrates how these individuals interact in a typical football club[16]. Club owners (shareholders) employ (or appoint themselves onto) a board of directors to oversee the running of the club. Usually the directors, although appointed by the shareholders, will have a stake in the club's affairs (see Table 3.2). Together the owners and the directors employ managers to work on their behalf. However, football clubs, and sports clubs in general, are unlike other

[16] Figure 3.1 applies mainly to the larger clubs. For smaller clubs the number of employees are usually much smaller and, therefore, the distinction between team matters and financial matters are not as straightforward.

businesses because the operations of the club can be separated into two distinct areas[17]. The left tier of Figure 3.1 relates to the on-field activities (playing side) of the business while the right tier is concerned with the financial side (off-the-field activities) of the business (i.e., commercial activities and ground management).

Figure 3.1 Structure of a Typical Football Club



For on-field activities, the football club appoints a manager to train, coach and select players. The manager may in turn appoint assistants, coaches and scouts to assist

[17] Diversified firms – firms which operate in more than one product market – can also be considered as having separate operations.

him in the decision-making process[18]. If the manager's function also includes the purchasing of players and negotiation of player contracts then the on-field activities will be influenced by off-field performance.

The distinction between on-field activities and off-field activities is of crucial importance to the analysis that follows. The following chapters focus on the on-field performance of the club (i.e., the highlighted boxes). We are, therefore, interested in the football team rather than the financial performance of the club. There are two reasons for this. Firstly, although financial output data is available (e.g., turnover, profitability), there is very limited information on the non-playing employees of the football club. Secondly, and more importantly, on-field success is the catalyst for off-field success. Consequently, although there is a high degree of correlation between percentage of games won and club profitability, all previous studies in this area have, quite rightly, focused on output measures that relate to the team's playing performance.

A further repercussion of the Premier League relates to the capital structure of football clubs. For many years football clubs were limited liability companies with the directors and chairmen forbidden to receive remuneration and dividends. The clubs themselves were owned by local business people and a few hundred small shareholders, usually fans, for non-monetary motives. Local business people, together with the financial support from the banking sector (i.e., loans and overdrafts), were the main sources of club finance. In recent times the dividends payable on shares has been relaxed (currently 15 per cent can be paid out in any one year) whilst clubs are now able to directly remunerate directors.

[18] The gender bias is deliberate (see Section 3.4.2). In some cases two (joint) managers are appointed.

Of most significance, however, is the number of clubs which are being financed by public share issue and the changing nature of football club ownership in general (Table 3.2). Six Premier League clubs have been successfully floated on the Stock Exchange (official list) since 1991. Two Division 1 clubs (Bolton and Sheffield United) also have listings and a third (Sunderland) has recently gained promotion back to the Premier League. A further seven clubs have floated on the alternative investment market (AIM) designed for young and growing companies, and two clubs (Arsenal and Manchester City) are listed on the OFEX (off the exchange) market. In total, the market capitalisation of football is valued at around £1,000 million (Deloitte and Touche, 1998).

Table 3.2 Ownership Structure of Premier League Clubs and other Listed Football Clubs

Name of Company (Club Name)	Listed/Unlisted	Value[a] £ million	Directors' Shareholdings		Number of Other Major Shareholders/Investors (total share capital holdings)[b]	Ownership Type[b]
			£ million	Per cent		
Arsenal Football Club plc	OFEX	154	134.75	87.5	N/A	Concentrated ownership
Aston Villa plc	Official List	55.5	19.43	35	N/A	Diversified ownership-concentrated control
Birmingham City Football Club plc	AIM	16.5	9.72	58.9	1 (6.6)	Diversified ownership-concentrated control
Blackburn Rovers Football and Athletic plc	Unlisted	25	N/A	N/A	1 (100)	Concentrated ownership
Burden Leisure plc (Bolton)	Official List	19.7	5.83	29.6	1 (16.1)	Diversified ownership-concentrated control
Charlton Athletic plc	AIM	16.5	10.23	62	1 (3.4)	Diversified ownership-concentrated control
Chelsea Village plc (Chelsea)	AIM	113.1	23.41	20.7	3 (62.8)	Diversified ownership-concentrated control
Coventry City Football Club (Holdings) plc	Unlisted	20	2	10	2 (62)	Diversified ownership-concentrated control
DCFC Limited (Derby County)	Unlisted	40	0.8	2	2 (94)	Concentrated ownership
The Everton Football Club Company	Unlisted	100	82.1	82.1	N/A	Concentrated ownership
Leeds Sporting plc (Leeds United)	Official List	47.6	1.67	3.5	6 (44.9)	Diversified ownership
Leicester City plc	Official List	14	5.95	42.5	N/A	Diversified ownership-concentrated control
The Liverpool Football Club and Athletic Grounds plc	Unlisted	180	107.28	59.6	N/A	Concentrated ownership
Manchester United plc	Official List	411.7	69.99	17	2 (9.4)	Diversified ownership
Middlesbrough Football and Athletic Company Limited	Unlisted	25	18.75	75	1 (25)	Concentrated ownership
Millwall United plc	Official List	4.7	N/A	N/A	N/A	N/A
Newcastle United plc	Official List	106.7	70.10	65.7	1 (3.6)	Diversified ownership-concentrated control
Nottingham Forest plc	AIM	23.2	12.78	55.1	2 (17.6)	Diversified ownership-concentrated control
Loftus Road plc (Queens Park Rangers)	AIM	7.2	1.84	25.6	6 (39.6)	Diversified ownership-concentrated control
Preston North End plc	AIM	8.6	0.12	1.3	6 (77.1)	Diversified ownership-concentrated control
Sheffield United plc	Official List	13.7	2.19	16	3 (12.1)	Diversified ownership
Sheffield Wednesday plc	Unlisted	46	2.62	5.7	1 (34)	Diversified ownership-concentrated control
Southampton Leisure Holdings plc	Official List	18.6	3.35	18	4 (31.9)	Diversified ownership
Sunderland plc	Official List	31.8	16.15	50.8	2 (8.1)	Diversified ownership-concentrated control
Silver Shield plc (Swansea)	Official List	N/A	N/A	45.4	1 (4.5)	Diversified ownership-concentrated control
Tottenham Hotspur plc	Official List	66.9	27.36	40.9	1 (4.1)	Diversified ownership-concentrated control
West Bromwich Albion plc	AIM	9.1	0.45	4.9	1 (9.3)	Diversified ownership
West Ham United plc	Unlisted	30	19.05	63.5	N/A	Concentrated ownership
The Wimbledon Football Club Limited	Unlisted	30	0.07	0.24	N/A	Concentrated ownership

Notes: AIM = Alternative Investment Market; OFEX = off the exchange (share dealings in unquoted companies).
[a] Market capitalisation for listed clubs as at 30/6/98. For unlisted clubs valuation based on Conn (1998).
[b] Adapted from Morrow (1999).

Even though the opportunity for widespread share-ownership has increased, the control of these clubs generally remains in the hands of the people (usually, directors) who controlled them before flotation. The club directors (columns three and four of Table 3.2) own on average 35 per cent of the total shareholdings of clubs floated either on the official list or on the AIM.

The retention of such archaic structures is partly historical, but the growth of institutional investment at a number of clubs[19] highlights the increasingly diverse nature of shareholders. A number of clubs have been the subject of take-over speculation, the most recent of which was the proposed take-over of Manchester United by BSkyB. And although the Monopolies and Mergers Commission rejected the deal the classification of ownership structure that exists in the football sector seems to be widening (column five). Three clubs, Manchester United, Leeds Sporting and Tottenham Hotspur, are classified as being 'owned' by city institutions (Morrow, 1999). Nevertheless, the majority of all other clubs not listed in Table 3.2 retain the traditional family/director control or dominant owner structure.

The most important aspect of the changing structure of football clubs may be its effect on the on-field activities of the team, specifically through the performance of the manager. One of the features of Chapter 1 was that the agency (hidden action) problem is exacerbated by the presence of multiple owners[20]. With multiple ownership the extent to which the manager can be held accountable for the firm's performance may diminish. The more widely shares are owned, the more likely managers will have an incentive to shirk. This is because without collective agreement each owner faces a free-rider

[19] Electra Fleming have a 25 per cent stake in Derby County; Charterhouse Tilney Securities have a £17 million stake in Sheffield Wednesday.
[20] Equally, the size of the club may have similar effects.

problem. Consider a situation where the manager is currently not monitored. If the shareholders wish to monitor the manager they have to spend some of their potential dividends on hiring supervisors. Now, if one shareholder decides to spend money on hiring a supervisor the increased effort by the manager, in terms of firm performance, will lead to increased dividends for all shareholders. However, a further problem is likely to occur. Even if monitoring was costlessly obtained, or could be collectively paid for, there may be disagreements as to whether the manager is shirking and whether the manager should be fired for shirking.

For the football manager the choice of whether to shirk or work is different from that faced by managers in other industrial sectors. Monitoring in football and the prospect of being dismissed is much greater so it is likely that the football manager has less incentive to shirk than his industrial counterpart[21]. Such constraints, however, may vary *within* the industry because, for example, some clubs may have a more relaxed policy on managerial turnover or the presence of multiple owners makes turnover more difficult (for reasons outlined above). Therefore the opportunity to shirk for some managers may be higher than it is for others.

3.4 Labour Inputs

The labour inputs in a football club are readily identifiable to most fans and paying spectators. Here we consider the role of players and the manager in team production, in particular the markets in which the services of players and managers are exchanged.

3.4.1 Playing Resources

The Retain and Transfer System

The ability to "transfer" players between clubs is another unique feature of football. Essentially players are treated as saleable assets in the same way as investment in physical capital (e.g., the club stadium); both generate income to the club over a number of years. However, whereas the performance of a machine can easily be measured the performance of human labour is more unpredictable because it is based partly on perceived ability (i.e., level and quality of experience) which can be measured, and partly on intrinsic ability which cannot. The uncertainty in player productivity is reflected in the variation in the transfer fees paid for the same player, even after accounting for the deterioration in performance brought about through age and injury. For example, Liverpool signed Stan Collymore from Nottingham Forest in June 1995 for a British record fee of £8.5 million. Two years later he was sold to Aston Villa for £7 million. Currently aged 28, and supposedly at the peak of his career, it is reported that his current (1999) value is less than £3 million.

For many years the employment of football players was based on the retain and transfer system. The principle behind the system is that the club holding the player's registration can demand a transfer fee from the buying club as compensation for the loss of service. Until the early 1960s the holding club had monopoly power over the player's registration. If a player wished to be transferred to another club the holding club had to agree to the sale. Moreover, the fee offered by the buying club had to be acceptable to the holding club. If the holding club refused the transfer request, or the fee offered, the

[21] The agency dimensions and ability characteristics of the manager are explored in Chapter 4.

player had no alternative but to remain with his present club (unless he wished to pursue a career outside of professional football). In 1963, George Eastham challenged his holding club's (Newcastle) decision not to allow him to transfer to Arsenal. The High Court ruled in favour of Mr Eastham on the grounds that the terms of the contract were a restraint on trade deeming the process *ultra vires*. This led to the adoption of a contract period and an option period of equal length whereby a club had to offer equally favourable terms in both the option period and the contract period. If the holding club did not offer such terms, or did not exercise the option, the player was free to move to another club for no fee.

Since 1977 players have had "freedom of contract". This allows a player to negotiate a move to a new club when his current contract expires. The holding club has the right to make a new contract offer to the player. But if the terms of the contract offered are not at least as good as in the final year of the contract the player can move to another club on a "free transfer" with no fee being paid. If the terms are as least as favourable, and the player still wishes to leave, or if the player is still under contract, a compensation fee is payable. If a fee cannot be negotiated by the clubs it is set by an independent tribunal, the Football League Appeals Committee (FLAC), comprising representatives from the League, Players' Football Association (PFA) and the League Managers' Association (LMA).

The player transfer system underwent a fundamental change in 1995. In September 1995 a Belgian footballer, Jean-Marc Bosman, brought a legal case against his holding club (RC Liège) for refusing to release him to the French club, US Dunkerque, principally because the French club could not afford the fee. The European Court declared that a club asking for a transfer fee for out of contract players was a restraint of trade (Article 48, Treaty of Rome), and ruled that all out of contract European Union (EU) nationals could move to another EU member-state with no transfer fee payable[22]. FIFA (soccer's world governing body) has since decreed that the directive should be extended to non-EU players. In England, complete free agency only applies once the player is over the age of 24 to allow for the investment costs (i.e., training and development) clubs incur during the early part of the player's career. If a player between the age of 21 and 24 changes club, having fulfilled the terms of the present contract but declining the offer of a new one, the selling club receives compensation at a level determined by the FLAC.

The Bosman ruling applies to out of contract players only. Transfer fees continue to operate where players wish to terminate a contract early. Historically, at least, most transfer activity takes place before the contract expires: 70 per cent of all permanent moves between 1990/91 and 1995/96 involved the payment of a fee (Dobson and Gerrard, 2000). It remains to be seen what the true cost of the Bosman ruling will be. Early indications are that employment contracts are being extended which, although providing security for the players imposes a pre-determined and costly commitment upon the clubs. Consequently, it is likely that all but the top clubs will continue to use relatively short-term contracts. Furthermore, Simmons (1997) predicts that the ruling is likely to result in a loss of transfer income to smaller clubs, higher salaries for the top players (see the next section on *wages and salaries*), and lower transfer fees in the long-run.

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[22] The restrictions on the number of foreign EU nationals playing for a particular club was also considered to be incongruous with Article 48.

Table 3.3 sets out the net transfer income (expenditure) of the 'average' club in each of the four divisions from 1992/93 to 1996/97. Since the inception of the Premier League the average top division club has consistently been a net purchaser in the transfer market whereas the average club in the lower divisions has generally been a net receiver. Interestingly, transfer expenditure seems to have risen post-Bosman[23] and the effect it has on the pre-tax profits of clubs is striking. In the Premier League alone the operating profit of £86.3 million (Table 3.1) was transformed into a pre-tax *loss* of £4.4 million for the 1996/97 season. However, the money spent by clubs in the Premier League is not filtering down to the lower division clubs. Increasingly the top clubs are purchasing players from overseas. Nearly 50 per cent of all transfer expenditure by Premier League clubs is paid to overseas clubs. For football as a whole, the overall financial state was a combined pre-tax loss of £42.6 million which would have been far worse had Manchester United not recorded a pre-tax profit of over £27 million (Deloitte and Touche, 1998).

Table 3.3 Net Transfer Fees Received (Paid) by the "Average Club" by Division (£,000)

Season	Premier League	Football League		
		Division 1	Division 2	Division 3
1992/93	(878)	(272)	49	84
1993/94	(1,109)	92	291	110
1994/95	(1,744)	75	(30)	36
1995/96	(5,278)	276	130	179
1996/97	(4,155)	(373)	238	114

Source: Deloitte and Touche (1998).

Not all transfers involve fees. Some transfers involve the exchange of a player or players either as a part replacement or complete replacement of a fee. Many moves take

[23] The most recent survey by Deloitte and Touche (1999) does however suggest that transfer spending has stabilised.

place on a temporary basis. In such cases a club "borrows" the services of the player agreeing to pay the player's wage whilst remaining registered to the holding club.

Under the laws of the Football Association, the transfer process of contracted players involves the holding club and the buying club but not the player or any other party, such as player agents. The direct involvement of the player (and his agent) is only allowed once a fee has been agreed between the two clubs. At this stage the buying club can negotiate personal terms with the player. This may involve offering incentive based inducements and perks (i.e., accommodation, car and so on) in addition to the basic salary, and in some cases the player may be offered a percentage of the signing-on fee. Once the player is signed the buying club pays a minimum 50 per cent of the fee immediately, with the remainder due within the following 12 months.

Even though players are the clubs major asset, for accounting purposes the recording of the payment (receipt) of transfer fees has been to debit (credit) fully within the financial year in which the transfer occurs. For example, when Newcastle purchased the services of Alan Shearer from Blackburn in July 1996 for a world record fee of £15 million, the cost was written-off completely in the profit and loss account for the financial year 1996. This generally has the effect of distorting the results presented in the financial statements particularly if the level of transfer activity is considered extraordinary.

A new accounting standard, Financial Reporting Standard (FRS) 10 on Goodwill and Intangible Assets, introduced at the end of 1998, stipulates that all clubs should write-off the transfer fee over the period of the contract, thereby capitalising the cost. The benefit of capitalisation lies in the improvements in comparing the club's financial statements; for Newcastle an operating profit of £5.9 million in 1996 was transformed into a pre-tax loss of £24 million. If the net transfer fees payable were excluded from this total the club would have generated a pre-tax profit of £3.6 million[24].

At present, FRS 10 has yet to be fully implemented by all football clubs. A number of clubs (e.g., Tottenham, Chelsea, Derby and Sunderland) record the cost of players' registrations on their balance sheets, but only include players acquired on the transfer market. Other clubs (Portsmouth, Bristol Rovers and Darlington) use directors' valuations. Conceptually, the transfer fee less an estimated sell-on value[25] is amortised over the length of the players contract. Under the terms of the standard, if the player suffers a serious loss of form during this time the asset is required to be re-valued.

Wages and Salaries

Football clubs also spend vast amounts of money on the wages and salaries of the players they employ. Taken with transfer expenditure, it accounts for the huge differences in club turnover and club profitability demonstrated earlier. The impact of the Bosman ruling has resulted in wages becoming the single largest expense for football clubs and these expenses continue to rise exponentially. This is demonstrated in Table 3.4.

[24] This is one reason why operating profit and not pre-tax profit was recorded in Table 3.1.
[25] The Bosman ruling has effectively resulted in clubs using a zero sell-on value.

Table 3.4 Wage Expenditure for "Average Club" by Division (£,000)

Season	Premier League	Football League		
		Division 1	Division 2	Division 3
1992/93	4,179	2,137	1,093	664
1993/94	5,312	2,609	1,086	708
1994/95	6,568	2,584	1,220	774
1995/96	8,145	3,294	1,376	922
1996/97	10,911	3,800	1,657	985

Sources: Deloitte and Touche (1996, 1997, 1998), Touche Ross (1995) and company accounts.

The Premier League had a wage bill close to £11 million during the 1996/97 season, over double the wage expense incurred during the 1993/94 season[26]. For the other divisions the growth rate is somewhat less; 75 per cent increase in Division 1 since 1992/93, and a 50 per cent increase in Divisions 2 and 3. Currently, approximately 50 per cent of a Premier League club's income and two-thirds of a Football League club's income is paid out in wages. The top players can command a salary of around £20,000 to £30,000 per week, although the average wage for a first-team Premier League player is much lower, about £4,000 per week. For the top players this is perhaps a conservative estimate given the wealth generating potential of endorsements. In the Football League, average earnings per week for the average player in each of the three divisions are £1,400, £500 and £325 respectively (Szymanski and Kuypers, 1999).

For the majority of players footballing careers are short. The average footballer starts his career as an apprentice around the age of 16. At the age of 18 the player, if considered good enough, will become a full-time professional. If he stays free from injury, the average player can expect to continue to play until the age of 32-34[27]. If the player is successful he may get transferred to a bigger (more successful) club and may

[26] The figures are slightly misleading because clubs are not required to break down wage costs into its constituent parts (i.e., playing and non-playing staff). We return to this important point in Chapter 4.

even gain representative honours and play in major international tournaments (European Championship and World Cup). Towards the end of his career, the player usually drops down divisions. In economic terms, the "success" of a player is represented by his transfer value and his level of wages[28].

During his career, a player will play, on average, two competitive matches per week. The other days are spent either training or relaxing. Unlike labour inputs in other industries, the performance of the professional footballer is observed by the employer and the customers[29]. This unique relationship is best portrayed by the PEP Report (1966) and applies as much today as it did then (perhaps more so):

> The first team player faces over forty public examinations a year before an attendance of thousands of spectators. He will be talked about, shouted at, criticised or praised, given extensive coverage in the press and radio...He is in the limelight and must be seen to behave as befits his profession. (p. 134)

However, even accounting for this unique relationship, players are still offered bonuses of various kinds to perform at their most efficient level. Additional payments may be made on the basis of number of appearances made, success in domestic and foreign cup competitions, promotion or league position, and crowd attendance. A player's performance is also influenced by the prospect of playing in the international team particularly in seasons when a major international tournament is due to take place.

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[27] This varies with playing position. For example, a goalkeeper's career can continue past the age of 40.
[28] The use of these measures as performance determinants is explored in Chapter 4.
[29] The same is also true of the manager.

3.4.2 Managerial Resources

The owner(s) of the club hires a manager to oversee the day-to-day operations of the club. The main function of the football manager is selection, supervision and coaching of playing staff and devising the team's tactics and strategies. Traditionally, the football manager has been also responsible for buying and selling players in the transfer market, negotiating wages with the players and some administrative duties. This dual role of the manager (acting as a team manager and a general manager) still dominates in the lower divisions. For the top clubs the manager is generally only responsible for the playing side with separate managers being appointed to oversee the business operations of the club (recall Figure 3.1). Managers at the top clubs are however in the limelight more and have to regularly deal with the press and the public.

Following the discussions of Chapter 1, the football manager requires many of the same characteristics as his industrial counterpart. The broad functions of interpersonal relations, information processing and decision-making, as defined by Mintzberg (1973) can be considered to apply to football managers as follows.

Firstly, interpersonal relations include the role of leadership and motivation. These are the most important characteristics that the manager possesses. The way the manager treats players in terms of verbal praise and criticism can affect not only the performance of the individual player, but also the performance of the team. Brian Clough has often been cited as one of the best motivating managers of the modern era. His performance at Derby and then at Nottingham Forest, winning 12 trophies in the process, was all the more remarkable because the two clubs did not have the financial fortunes of the bigger clubs. He achieved this success using a mixture of generosity and humiliation. On the one hand his training methods were renowned for being the least strenuous in the league and he was the first manager to introduce the mid-season break. On the other hand:

> He had this uncanny knack of humiliating people in front of their peers...Trevor Francis, the man Clough made the first million-pound player, made his debut for the A team and then spent his first senior games making tea at half-time! (King and Kelly, 1997, pp. 121-122).

Using match reports and videos to analyse and assess player performances in order to formulate plans and strategies are aspects involved in the information processing role. The manager may also employ assistants, coaches and scouts in order to disseminate information and delegate responsibility. Finally, as a decision-maker the manager organises the team (e.g., team formation) and the role of individual players (e.g., Campbell marks Owen) both before and during the game (e.g., half-time team talk and strategic substitutions). The manager's ability to respond to situations as and when they arise (e.g., a player suffers a loss of form or a bad injury) can make the difference between the club achieving its objectives and not achieving what was expected.

The vast majority of managers are ex-professional footballers. The prerequisite of a playing career is usually the only source of experience for most managers, although some come into management having been a coach, assistant manager or player-manager. Very few come into management without some kind of involvement in the game. Given that most managers are ex players (whose careers begin at age 16) educational training ceases soon after leaving school. The absence of further and higher educational qualifications for football managers contrasts sharply with the level of schooling achieved by managers in other industrial sectors. In a recent Labour Force Survey 46 per cent of all managers questioned had a higher education qualification and, only 10 per cent are classified as having no qualifications (Labour Market Trends, June 1998).

There also seems to be a disparity between industrial managers and football managers in terms of formal labour market training. Whereas the majority of industrial managers have had some formal training (see the empirical studies cited in Section 1.8), relatively few training opportunities exist for the football manager. The Football Association does organise coaching courses, but most managers rely on their experience gained as a player, believing that playing experience is interchangeable with managerial performance. In recent times, however, the emphasis does seem to be changing. Courses that aim to teach football players how to become football managers have been established at the Universities of Central Lancashire and Greenwich. The courses provide advice on developing the necessary managerial skills outlined earlier and stress management. Whilst the courses seem to have been well received by a number of players coming to the end of their playing careers, the majority of managers still rely on practical experience.

There are other features which distinguish the football manager from his industrial counterpart. Firstly, football management remains 100 per cent male. Secondly, Table 3.5 shows that football managers assume responsibility at a younger age but seldom continue past the age of 55. Nearly 50 per cent of team managers operating during the 1997/98 were between 35 and 44 years of age. The comparable figure for industrial management is only 23 per cent. More significantly, only 4 per cent of football managers are over the age of 55 compared to 36 per cent in other industries.

Table 3.5 Age Distribution of Industrial

and Football Managers (Per Cent)

Age	Industrial Managers	Football Managers
<35	15.9	8.3
35-44	23.0	49.1
45-54	25.3	38.9
55-64	17.5	3.7
65+	18.3	0

Sources: Adapted from Labour Market Trends (June, 1998), Rothmans Football Yearbook (1998) and Turner and White (1993)

Thirdly, and perhaps crucially, the football manager faces continual job insecurity. Table 3.6 lists the total number of terminations and the timing of these terminations between the seasons 1992/93 and 1997/98. It shows that on average over one third of clubs change their manager every year and three-quarters of the changes take place during the football season. A more detailed analysis based on the division in which the club was competing at the time of the termination is provided in Table 3.7. The prospect of job separation is greater in the lower divisions, with managerial turnover being highest in Division 3 (an average of 13 terminations per season). In contrast, the average number of terminations in the Premier League is seven per season[30].

[30] The high number of terminations which occurred during the 1994/95 season could be partially explained by clubs simply changing manager because almost everyone else has (i.e., the "bandwagon effect").

Table 3.6 Number of Managerial Terminations and Timing of Terminations, 1992/93 to 1997/98

Season	Number of Clubs Terminating[a]	Timing	
		Mid-Season	Post-Season
1992/93	34 (6)	24	16
1993/94	34 (1)	28	7
1994/95	50 (10)[b]	48	14
1995/96	31 (5)	28	8
1996/97	36 (5)	31	10
1997/98	39 (8)	36	11

Sources: Rothmans Football Yearbook (1998) and Electronic Telegraph.
[a] Figure in parenthesis refers to the number of clubs who changed manager more than once (including post season terminations).
[b] Includes Cardiff City and Notts County who changed manager three times.

Table 3.7 Managerial Termination by Division, 1992/93 to 1997/98

Season	Premier League	Football League		
		Division 1	Division 2	Division 3
1992/93	4	13	8	15
1993/94	7	10	8	10
1994/95	14	16	14	18
1995/96	3	11	10	12
1996/97	7	11	11	12
1997/98	9	14	15	9

Sources: As Table 3.6.

Most of the terminations are involuntary (the manager is dismissed) rather than voluntary (he quits to take a position at another club). The criterion of managerial ability is usually measured in terms of the short-term "success" of the club where success could mean winning competitions or gaining promotion, avoiding relegation or even maintaining the solvency of the club. However, given the nature of the product all managers measured in these terms cannot be successful.

Once a manager is dismissed it is usual for the assistant (if there is one) or a caretaker manager to take control of team affairs for a temporary period until a new manager is appointed. This can take anywhere between one day and a full season. Once dismissed, however, it is not uncommon for a manager to be re-hired into a comparable position at another club, often within a short space of time. This peculiar aspect of job mobility may simply be the result of some managerial experience being better than none at all. Or a club may find itself requiring a manager with experience on a short term basis (e.g., Ron Atkinson was considered adept at saving clubs from relegation). Alternatively it may simply reflect the matching process - it takes a club many 'unsuccessful' attempts to find the 'right man for the job'.

3.5 Summary

The economic performance of the football industry in the late 1990s is almost unrecognisable from that of 10-15 years before. On-the-field, apart from a few minor rule changes, things are more or less the same: players and management of two teams combine to provide a product (the game). However the structural changes that have taken place at both the industry and club level have increased the demands for success from the owners, investors, sponsors and fans. And while the financial rewards to players are at unprecedented levels, managers in the industry now face the kind of pressures that are familiar to managers in other industrial sectors.

Managers are frequently assessed in terms of on the field success and the high managerial turnover in the industry is a consequence of this. In the following chapter we develop a formal model for determining and evaluating the performance of the football manager which takes explicit account of the quality of the playing resources he has at his disposal. This will give us an improved measure of managerial quality since it does not simply measure performance in terms of playing success.

CHAPTER 4

MODELLING FOOTBALL PRODUCTION AND MANAGERIAL EFFICIENCY

4.1 Introduction

In the previous chapter we argued that the football industry is well suited to a study of performance evaluation because output (results of matches) and inputs (players and manager) are unambiguously measured, well documented and not subjected to the same kind of disclosure problems that characterises other industries. Furthermore clubs compete under the same rules and regulations and share a common technology. Along with the players managers are an integral part of the production process in football[1]. The football manager is the key decision-maker in the production process – his role is to transform a given set of playing resources into team wins. The extent to which this is done successfully has not been documented in a meaningful way until now.

In order to be able to quantify the manager's contribution to team output and measure his performance relative to the best practice we need to develop a formal model of the production process. Our formal model is developed in three stages. Team performance is a function of the quality of the team and the skill of the manager. In the

[1] Recall that the production process is based on the sporting activities of the football club - and therefore the team - rather than the financial activities. See Chapter 3 for details.

first stage we consider two methods for determining the quality of the playing resources. Ideally the measure of team performance should be based on actual performance inputs. However, the data in English professional football are not as extensive as in North American sports so the method used to measure team performance differs from those adopted in previous studies. Two market-based measures of team quality are considered as proxies for unobserved individual player productivity: one is based on recorded wage data, the other on a predicted player transfer valuation.

Once we are able to measure team quality we can use stochastic frontier analysis to measure the efficiency or performance of the manager (see Chapter 2). Essentially this involves treating the manager as a residual concept in the team production function. Each manager is assessed according to the maximum potential wins that his team can achieve given the quality of the players and other random factors. Estimation of a production frontier enables us to calculate an efficiency score - the closer the manager gets to the maximum potential number of wins the higher his efficiency score will be. In Section 4.3 we explain why we use this particular estimation technique and outline the theory involved in deriving the estimates.

Having generated efficiency scores, the third and final stage involves evaluating the managerial efficiency scores. That is, we seek to understand why efficiency varies by manager. To do this we integrate the ideas of agency theory and human capital theory (considered in Chapter 1) into a formal model of managerial production so that we can test whether managerial performance is determined by ability and effort incentives.

4.2 Modelling Team Production in Football

Recall from Chapter 2 that the production process in football is the individual match. Each team is involved in a constant number of league[2] matches per season, and overall team success can be measured either by the percentage of matches won in a season (win ratio) or the percentage of points gained in a season (points ratio). This latter measure determines the team's final league placing. Success in any given season depends on the quality of the playing resources and the performance of the manager. Formally:

$$Y_{it} = Y_{it}\ (Q_{it}^{T}, P_{it}^{M}) \tag{4.1}$$

where Y_{it} represents team winning percentage or team point percentage for the i-th team in the t-th season; Q_{it}^{T} is the quality measure(s) of the playing inputs for the i-th team (T) in the t-th season; and P_{it}^{M} is the measure of manager performance. As will be demonstrated in Chapter 5, the quality measures are normalised by the mean value by league for each year (i.e., $(Q_{it}^{T})^{*} = Q_{it}^{T} / [1/n(\sum_{i,t}^{n} Q_{it}^{T})]$).

$Y_{it}\,(\cdot)$ is assumed to be the same for all teams because each team plays to a certain set of rules and they share a common production technology[3]. In addition it is assumed to satisfy all the requirements of a neo-classical production function (i.e., quasi-concavity and twice continuously differentiable). The model appears to be fairly restrictive because

[2] Cup competitions such as the FA Cup, League Cup and European Cups also add to the success of the team. However, success in cup competitions is much more unpredictable because of the random nature in which teams are drawn to play each other. In contrast, the league title is awarded for consistent performance over a period of eight months (the football season runs from August to May) with each team playing each of the other teams in the league twice (home and away).

[3] Teams do, however, play in stadia of varying degrees of size and quality (e.g., Old Trafford versus Boothferry Park). The impact of home advantage is beyond the scope of this study.

it excludes other possible inputs in the production process such as coaches[4], team scouts and ownership effects. However, we will argue later in the chapter that ownership influences the performance of the manager rather than the performance of the players. Also, crediting the manager for coaching and team scouting is justified because managers choose and organise their support staff. Thus, the skills of the support staff reflect the manager's decision-making ability.

4.2.1 Measuring the Quality of the Playing Inputs

Associated with each individual player is a certain amount of playing skills. In football these skills include: the ability to pass, shoot and head the ball, speed, agility, strength, awareness, concentration and determination. Such attributes are often innate, although the player through investment in training and development can acquire some attributes. The football team is composed of 11 starting players in a variety of positions[5] playing under a formation determined by the manager. Each game lasts 90 minutes within which time a number of substitutions (strategic or otherwise) are allowed. Competition often ensues between players for the limited number of starting places, and the manager may rotate his squad - generally anywhere between 16 and 30 players - to maximise collective performance and to stimulate competition. Competition also derives from players who play in similar positions in other clubs who can be traded. Scully (1995) refers to this as a serially repeated rank-order tournament that results in improved performance by the individual whose place is under threat, *ceteris paribus*.

[4]In the North American literature especially the manager is referred to as the coach.
[5] Broadly speaking these are goalkeeper, defenders, midfielders and forwards (strikers).

In professional team sports players interact with one another and interaction is essential to team performance. The classic problem in a team sport such as football is trying to evaluate the performance of a player independently of the performance of his teammates and the manager. When a striker scores a goal, the midfield player who supplied the pass and the second striker who created the space get no statistical credit. To simplify matters team quality is assumed to be the linear summation of the skills of the individual players. This means the playing inputs are separable (additive) so the cross-partial derivative between, for example, player 1 and player 2 is zero i.e., $\frac{\partial^2 Q^T}{\partial q^1 \partial q^2} = 0$. Therefore:

$$Q_{it}^T = \sum q_{it}^1 + q_{it}^2 + q_{it}^3 + \ldots\ldots + q_{it}^n \qquad (4.2)$$

Consequently nebulous terms such as team spirit and player externalities are ignored. The important point to note here is that teams may perform better when certain players are playing. For example, much of Manchester United's recent success has been attributable to the performances of Peter Schmeichel and Eric Cantona. It has often been said that Peter Schmeichel was "worth" about 12 points per season (i.e., Manchester United win six games they should have drawn or four games they should have lost). When Blackburn won the Premier League title in 1994/95 much was said of how much Manchester United missed the influential skills of Eric Cantona. Our inability to account for these aspects may overstate (understate) the contribution of the manager in the presence of positive (negative) team effects. However, the linear summation of playing inputs is a well established assumption in the North American literature (e.g., Quirk and

El Hodiri, 1974)[6]. Therefore the linear summation assumption will remain for the purposes of this study[7].

There are a number of different ways we can measure the playing inputs in the team production function.

4.2.2 Individual Performance Data

In this approach team success is regressed on actual performance inputs. In the North American literature team success is based on win ratio because in team sports there are no, or very few, drawn matches. On the input side several (competing) measures of individual input exists. In baseball, for example, hitting and pitching are the most important performance indicators. Hitting has often been measured as batting average, total runs scored or slugging percentage (such as total bases divided by at bats). The most commonly used measures for pitching include earned run average and the strikeout-to-walk ratio. Although *a priori* there seems little to distinguish these and other competing performance measures, the appropriate choice has usually been justified on empirical grounds. Team contribution is then calculated by aggregating these measures across individuals using equation (4.2). Because baseball has the richest laboratory of data, and because cross - player contribution is significantly less, much of the literature

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[6] Carmichael and Thomas (1995) use the average number of appearances made by each player as a possible team contribution effect. Theirs is the only study which has attempted to include team effects.
[7] Preliminary work did test for the following team contribution measures: absolute number of players used; absolute number of players used which conform to the appearance criteria - the idea being that only those players that could have a potentially significant effect on the team's success should be included; average number of appearances made by all players; average number of appearances made by players who conform to the appearance criteria; total number of players who played for this team in the previous season and total number of players who played for this team in the previous season who also conform to the appearance criteria this season. None were significant at the 5 per cent level.

surveyed in Chapter 2 is in this area. Comparable measures of performance are, however, available in American basketball (e.g. Zak *et al.*, 1979, include nine 'separate' team input variables) and, to a lesser extent, American football.

In contrast to the myriad of statistics available in North American sports, there is a lack of recorded data on English professional football on most playing aspects of the game (e.g., successful passes, shots on goal, tackles made and shots blocked). The only individual player output measures available at present are the number of appearances made and number of goals scored[8].

4.2.3 Wage Data

In the absence of suitable individual player performance data, Szymanski and Smith (1997, hereafter SS (1997)) estimate a football production function regressing team success on players' wages, although, as we will demonstrate later, the way the data is recorded means that it is not based on individual player wages. Nonetheless, such an approach requires competition in the labour market so that the player's wage is equal to his marginal revenue product (MRP), enabling the wage to proxy for non-measurable performance indicators.

However, for many years the mobility of footballers was limited because of the league's rules on the hiring of players. These rules, such as the maximum wage and the

[8] The Opta Group has recently begun to analyse the performance of FA Premier League footballers. ('Fantasy Leagues' also contain certain aspects of player performance.) The Opta index was launched in September 1996 to provide data on most of these previously unmeasured aspects in order to be able to fully assess the performance of individual players. However, it is restricted to Premier League teams

retain and transfer system[9], although justified on the grounds of promoting competitive balance, effectively gave clubs a property right over the player's services, thus creating a purely monopsonistic factor market. Similar arrangements exist in American team sports with the reserve clause in baseball and the rookie draft in American football. The degree of player exploitation is a consequence of the "tightness" of these labour market controls and has been tested empirically in a number of studies (e.g., Scully, 1974; Medoff, 1976).

The effects of monopsony power on player wages and employment levels are illustrated in Figure 4.1. Under a monopsonistic market structure there is a single buyer of the playing inputs due to collusion of the individual clubs (acting as a joint monopsonist) with each club facing an upward sloping market supply curve of playing talent (S_q). The individual clubs must pay a higher wage to attract additional players, so the marginal cost of labour curve (MCq) is always and everywhere above the supply curve. The supply curve is relatively inelastic to reflect the highly specialised talent and skills possessed by the players (i.e., high entry barriers). The demand for players in football is based on each player's MRP curve which is downward sloping to reflect diminishing returns. For simplicity we assume homogeneity of the playing inputs. The results are little changed if we incorporate player heterogeneity into the analysis, although the horizontal axis should now be measured in terms of standard efficiency units because of differences in skill (Sloane, 1969). For the monopsonist, the optimum quantity of players is found where MCq = MRPq. This corresponds to q_2 units of playing talent at a wage w_2. The monopsonistic profit or degree of exploitation is represented by the shaded area (i.e., the difference between w_2 and w_3 multiplied by q_2)

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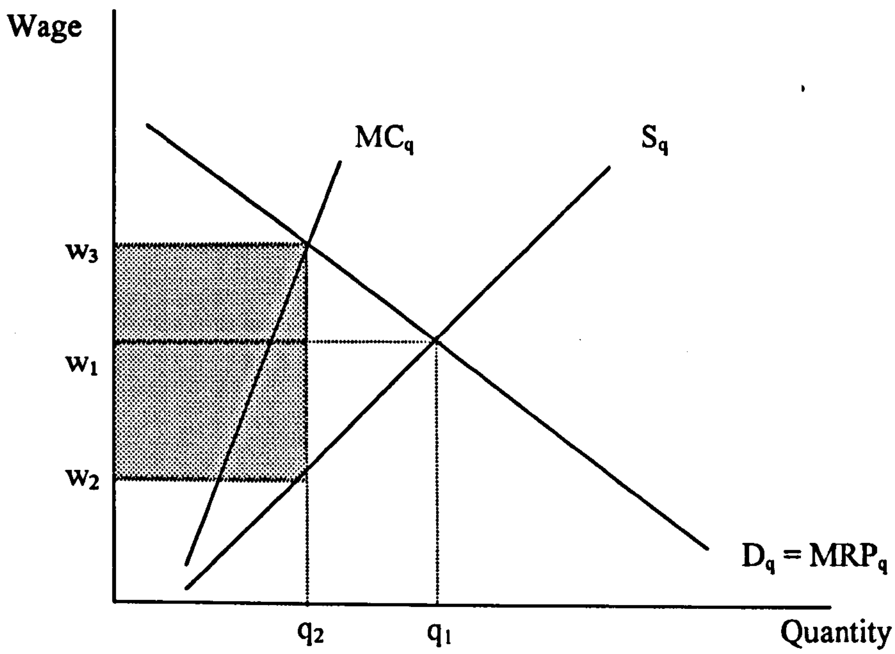
and data is only available for the 1996/97 and 1997/98 seasons (resulting in a fairly modest sample size), thus proving unsuitable for our purposes.

[9] See Chapter 3 for an historical account of these restrictive measures.

because although each player's contribution to the club's revenue is w_3, each player is only paid w_2.

Figure 4.1 Wage and Employment Determination in Professional Football



The demise of the player reservation system in football has significantly reduced the monopsony power of clubs, resulting in a more competitive market for players. In a competitive market Sq = MCq. The wage paid to the players is now w_1, the amount of labour hired increases to q_1 and the club no longer exploits players because the shaded area is transferred to the players. Each player's wage now approximates his MRP. Sommers and Quinton (1982) show, in the context of North American sports, that the removal of restrictive controls leads to the transfer of monopsony rents from the clubs to the players (so that the wage approximates the MRP). SS (1997) refer to this as player market efficiency. Support for such a hypothesis in English football is presented by Szymanski and Kuypers (1999).

However, if the objective of the club owners is utility rather than profit maximisation, it does not follow that players are necessarily exploited even under a player reservation system. A utility maximising club that attaches a high value to playing success relative to profit may choose to sign players for salaries higher than their MRP in an attempt to increase playing success, even though it is not profitable to do so. We have already noted that many football clubs continue to incur financial losses (see Table 3.1). Financial losses could also occur because the quantity of labour hired exceeds the profit maximising level[10]. Therefore given utility maximisation the traditional supply and demand model is not that useful when applied to football clubs.

As well as theoretical problems there are also empirical concerns over the use of wage data to measure team quality in English football. To begin with wages and salaries are recorded at the aggregate level. This kind of classification means that the wage recorded in the club's financial accounts includes not only the players' wages but also those of all other staff employed by the club (see Figure 3.1). As a result, any analysis that proposes to measure the contribution of the manager residually using wage data is conceptually incorrect[11]. Secondly, the recording of wage data is not reliable and is often not available at all for a number of smaller clubs. Approximately 25 per cent of clubs each season do not disclose a complete set of financial data. Finally, even where complete information exists there are differences in the accounting policies of clubs[12].

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[10] Dobson and Gerrard (2000) show formally that a utility maximiser employs a level of playing talent above that consistent with profit maximisation. A similar result is found by Vrooman (1997) in North America where teams are run by 'sportsman-owners'.

[11] The largest percentage of the salary bill is, however, paid to the players.

[12] This is also prevalent in the treatment of the valuation of players and transfer expenditure/receipts.

4.2.4 Individual Player Transfer Valuations

If the labour market in football is competitive we can use the player's predicted transfer valuation as a quality indicator. As highlighted in Chapter 3, the treatment of football players as saleable assets is unique to professional sports[13] and the data provided by the transfer valuations of players can be used as a proxy for performance. In effect the player's predicted transfer value reflects, among other things, aspects of the player's ability and, whereas wage data is recorded at the aggregate level, transfer valuations are available at the individual player level.

A number of studies have found that observed transfer fees are determined by (i) the characteristics of the player; (ii) the characteristics of the buying club; and (iii) the characteristics of the selling club. Generally the studies follow a similar empirical methodology but differ in their interpretation of the outcome of the fee. SS (1997) argue that players are bought in a competitive market. On the other hand, Carmichael and Thomas (1993) and Dobson and Gerrard (2000) argue that the transfer fee is the result of a bargaining process with the negotiated fee lying somewhere between the selling club's reservation price and the buying club's maximum offer price. These two approaches can be considered as alternative views on the degree to which fees involve monopoly (or monopsony) rents. Under SS's interpretation there are no rents because the transfer fee is set at the selling club's reservation price. However, Carmichael and Thomas and Dobson and Gerrard argue that the outcome results in monopoly rents since the fee is established above the selling club's reservation price.

[13] In effect the process which allocates the players is distinctly separate from the wage bargaining process.

Following the work of Dobson and Gerrard, a SOCCER TRANSFERS program has recently been developed by Bill Gerrard to estimate individual player transfer valuations. In addition to the player characteristics originally considered by Dobson and Gerrard, SOCCER TRANSFERS includes aspects relating to the divisional status of the player, type of international experience (i.e., European or South American) and divisional distribution of league experience[14]. We have used this program to generate a predicted transfer value for each player in each team.

Although the characteristics of the individual players can be uniquely determined, fairly restrictive assumptions need to be made about the potential buying club and selling club because only a small proportion of players are actually transferred each season. The buying club is assumed to be mid-division (measured by position and average gate) based on the club's current divisional status. The selling club is also assumed to be mid-division but based on the player's divisional status at the end of the previous season. This is obviously restrictive. One would not expect a player of the calibre of Michael Owen (given current form) to be sold to the 'average' club, i.e., Derby County (based on information from the 1997/98 season). Conversely, one is more likely to find players coming towards the end of their careers dropping to lower divisions. A good example of this is Neville Southall who was transferred from Everton (Premier League) to Stoke (Division 1) and who has since moved to Doncaster (Conference League). The valuation here would be over-estimated given the buying club characteristics because at the start of the season he was still contracted to the Premier League club[15].

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[14] Further details of the software package are provided in Chapter 5 and Appendix I.

[15] Based on the 1997/98 season. In Appendix I we evaluate how reliable the model is at predicting actual transfer fees and the appropriateness of the model as a productivity measure.

Nevertheless the homogeneity assumption eliminates any potential biases which could be caused by arbitrarily deciding on buying club characteristics. The selling club restrictions are necessary because we wish to isolate the effects of the player's characteristics on the predicted fee.

Formally, the estimated player transfer value is obtained from the following specification:

$$PV_{it}^{P_j} = PV_{it}^{P_j}(C_{it}^{P_j}, \overline{S}_{it}, \overline{B}_{it}) \qquad (4.3)$$

where $PV_{it}^{P_j}$ is the predicted transfer value of the *j*-th player at the *i*-th club in the *t*-th season; $C_{it}^{P_j}$ is a vector of player characteristics relating to historical and current performance (e.g. appearances, goals scored, international honours); $\overline{S}_{it}$ is a mid-division selling club based on player's divisional status in previous season (*t*-1); and $\overline{B}_{it}$ is a mid-division buying club based on position and average gate of club's current divisional status.

As an example consider the baseline valuation (*VALUE 1*) of the SOCCER TRANSFERS program[16]. Using the buying and selling club assumptions outlined above, the player's predicted valuation is based on the following linear equation:

$$VALUE\ 1 = \beta_0\ \beta_1 LEAGTOT_{it}\ \beta_2 GLSTOT_{it}\ \beta_3 PREVCLUB_{it}\ \beta_4 AGET_{it}\ \beta_5 TOTLGT$$
$$\beta_6 GLST_{it} + V_{it} \qquad (4.4)$$

In equation (4.4), *LEAGTOT* and *GLSTOT* are career league appearances and career goals; *PREVCLUB* is the number of previous clubs played for (including loan spells); *AGET* is the players age in years and months and *TOTLGT* and *GLST* relate to current league appearances (t-1) and current league goals (t-1). A fuller description of each of these variables together with other valuations considered (including aspects relating to divisional status and international experience) are provided in Chapter 5.

The valuations of each player generated in equation (4.3) or equation (4.4) will vary season by season, depending on the player's current form - goal-scoring ability, ability to stay free from injury, gaining international appearances and possibly whether the player is on a short-term or long-term contract[17]. The team quality measure is based on the linear summation of the predicted player transfer valuations ($Q_{it}^{T} = \sum PV_{it}^{P_1} + PV_{it}^{P_2} + \ldots + PV_{it}^{P_n}$).

Wages is the only available alternative input measure to estimated player transfer valuations. It is included in the empirical section because it allows us to analyse the extent to which the efficiency scores are sensitive to alternative input measures (see Chapter 6 for details). But because of the way the wages data is compiled we must strike a note of caution regarding its reliability in the production frontier estimation. The wage equation is specified as:

$$W_{it}^{C} = W_{it}^{C}(W_{it}^{T}, W_{it}^{M}, W_{it}^{E}) \qquad (4.5)$$

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[16] Note *VALUE 1* = $PV_{it}^{P_j}$.

[17] The idea is that players who have long-term job security are likely to exert less than the maximum amount of effort. Krautmann (1990), however, argues that effort is often confused with stochastic player

where W_{it}^{C} measures the total wage and salary costs for *i*-th team in *t*-th season; W_{it}^{T} measures player wage costs; W_{it}^{M} measures management wage costs; and W_{it}^{E} measures total wage cost of all other employees. The individual components of equation (4.5) are not recorded separately.

Substituting equation (4.3) or equation (4.5) into equation (4.1) gives the following empirical team production functions:

$$Y_{it} = \beta_0 + \beta_1 PV_{it}^{T} + \beta_2 P_{it}^{M} + V_{it} \tag{4.6}$$

$$Y_{it} = \beta_0 + \beta_1 W_{it}^{C} + \beta_2 P_{it}^{M} + V_{it} \tag{4.7}$$

As before the subscripts *i* and *t* represent the *i*-th team and the *t*-th season of observation respectively; P_{it}^{M} is the measure of manager performance; and V_{it} is a standard random element term which captures measurement error and omitted variables (e.g., home advantage, weather conditions and size and vocal support of the crowd).

4.3 Measuring Managerial Efficiency

In Chapter 1 we said that previous attempts at measuring managerial performance (P_{it}^{M}) have been mainly based on either indirect measures of performance (i.e., firm performance or wages) or subjective measures of performance. Here individual efficiency scores for each manager in each season are obtained using the technique of

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performance; what appears to be contract related player shirking is actually the result of the stochastic nature of performance.

stochastic frontier analysis. As noted in Chapter 2, this approach is also a significant departure from most of the previous production frontier studies in sport which tend to favour a deterministic approach. The reason for favouring the stochastic approach is because the player quality measures are only proxies for "true" performance measures. As a result measurement error is likely to play a bigger role here than in previous non-football sports studies. Managerial efficiency is treated as a residual concept and is evaluated in terms of "getting the most out the playing resources"; the better (more efficient) managers are able to transform a given set of player quality into more wins, points or a higher league position than the average manager[18].

The production frontier equivalents of equations (4.6) and (4.7) are:

$$Y_{it} = \beta_0 + \beta_1 PV_{it}^T + V_{it} - U_{it} \tag{4.8}$$

$$Y_{it} = \beta_0 + \beta_1 W_{it}^C + V_{it} - U_{it} \tag{4.9}$$

where V_{it} - U_{it} is the residual component, and U_{it} is the managerial performance (efficiency) term such that $U_{it} = P_{it}^M$. Otherwise variables are defined as before.

As mentioned in Chapter 2, the choices available to estimate (managerial) efficiency depend on the type of data available. With cross-section data we could use COLS or ML. When panel data are available the efficiency scores can be derived using fixed effects (e.g., within estimator) or random effects (e.g., GLS or ML). Here, and in Chapter 5,we use the ML version as applied to cross-section data for the purposes of

[18] Managers can also be assessed in terms of recruitment efficiency: the ability to find "bargain" players who demand a high resale value. This suggests that total (managerial) efficiency is based on improving team performance with a given set of players and making resource allocation decisions over time to

illustration. In Chapter 6 we test statistically which model is preferred when panel data is available (within, GLS or ML).

In order to estimate U_{it} using ML methods, it is necessary to specify the distribution of the residual components:

$$V_{it} \sim N(0, \sigma_V^2) \tag{4.10}$$

and

$$U_{it} \sim N(0, \sigma_U^2) \tag{4.11}$$

To simplify expressions that follow here and in Chapter 5 we drop the subscripts *i* and *t* and we replace PV_{it}^T or W_{it}^C with Q^T. The density functions which correspond to equations (4.10) and (4.11) are defined as:

$$f(V) = \frac{\exp -\frac{1}{2}\left(\frac{V}{\sigma_V}\right)^2}{\sigma_V \sqrt{2\pi}} \qquad \text{for all } V \tag{4.12}$$

$$g(U) = \frac{2}{\sigma_U \sqrt{2\pi}} \exp -\frac{1}{2}\left(\frac{U}{\sigma_U}\right)^2 \qquad \text{for } U \geq 0$$

(4.13)

$$= 0 \qquad \text{otherwise.}$$

improve future team performance and club profitability. Recruitment efficiency is beyond the scope of this thesis.

These are the normal and half-normal distributions. Alternatively, the efficiency term can follow the truncated-normal distribution[19]:

$$U \sim N(\mu, \sigma_U^2) \tag{4.14}$$

This corresponds to a density function defined as:

$$g(U) = \frac{\exp\ -\frac{1}{2}\left(\frac{U-\mu}{\sigma_U}\right)^2}{\sigma_U\left(1-\Phi(-\mu/\sigma_U)\right)\sqrt{2\pi}} \qquad \text{for } U \geq 0$$

$$= 0 \qquad \text{otherwise.} \tag{4.15}$$

$\Phi\ (\cdot)$ represents the distribution function for the standard normal random variable. If we let $\varepsilon = V - U$ and U follows a half-normal distribution, whilst assuming the model specification is based on T = 1 and $\mu = 0$[20], then the joint density function for ε is given as:

$$h(\varepsilon) = \int_0^\infty g(\varepsilon - U) f(U) \partial U \tag{4.16}$$

Following Aigner, *et al.* (1977), this can be written as:

$$h(\varepsilon)\big|_{\mu=0} = \frac{2}{\sigma_U + \sigma_V}\phi\left(\frac{\varepsilon}{\sigma_U + \sigma_V}\right)\left[1 - \Phi\left(\frac{\varepsilon\sigma_U}{\sigma_V(\sigma_U + \sigma_V)}\right)\right] \tag{4.17}$$

[19] Other distributions exist (e.g., exponential and the gamma) but the half-normal and the truncated-normal are the most commonly used in empirical studies.

where ϕ is the standard normal density function.

The density function for Y is found by replacing ε with $Y - \beta_0 - \beta_1 Q^T$:

$$h(Y)\big|_{\mu=0} = \frac{2}{\sigma_U + \sigma_V}\phi\left(\frac{Y - \beta_0 - \beta_1 Q^T}{\sigma_U + \sigma_V}\right)\left[1 - \Phi\left(\frac{(Y - \beta_0 - \beta_1 Q^T)\sigma_U}{\sigma_V(\sigma_U + \sigma_V)}\right)\right] \tag{4.18}$$

Details of the theory underlying the ML estimation of a production frontier for cross-section (single-season) data can be found in Chapter 5.

Once the production frontier estimates have been obtained, the next stage involves calculating the individual efficiency scores. Recall from Chapter 2 that (technical) efficiency is measured relative to the stochastic production frontier:

$$TE = \frac{\beta_0 - \beta_1 Q^T + V - U}{\beta_0 - \beta_1 Q^T + V} \tag{4.19}$$

Mean efficiency is obtained by substituting:

$$E(U) = E(\varepsilon) = \left(\frac{2}{\pi}\right)^{1/2} \sigma_U \tag{4.20}$$

into equation (4.19).

[20] Generalisations of this model are provided in Chapter 6.

Estimating individual efficiency requires decomposition of efficiency from noise. Following Jondrow *et al.* (1982) this can be achieved using conditional probability of the inefficiency term given the composed error:

$$E(U|\varepsilon) = -\gamma\varepsilon + \sigma_* \left[\frac{\phi(\gamma\varepsilon / \sigma_*)}{1 - \Phi(\gamma\varepsilon / \sigma_*)} \right] \tag{4.21}$$

where $\sigma_* = \sigma\sqrt{\gamma(1-\gamma)}$.

If the production frontier is specified in logarithmic form, such as Cobb-Douglas, equation (4.8) and equation (4.9) can be expressed as:

$$\ln Y = \ln \beta_0 + \ln \beta_1 Q^T + V - U \tag{4.22}$$

(Technical) efficiency can be measured as:

$$TE = \exp(-U) \tag{4.23}$$

Mean efficiency is obtained by:

$$E(\exp(-U)) = 2[1 - \Phi(\sigma_U)]\exp\left\{\frac{\sigma_U^2}{2}\right\} \tag{4.24}$$

and individual efficiency is defined by:

$$E[\exp(-U)|\varepsilon] = \exp\left(\gamma\varepsilon + \frac{\sigma_*^2}{2}\right)\frac{1 - \Phi[\sigma_* + \gamma\varepsilon/\sigma_*]}{1 - \Phi(\gamma\varepsilon/\sigma_*)} \tag{4.25}$$

Equation (4.25) is a non-linear form of equation (4.21). Jondrow *et al.* argue that equation (4.21) can be used to estimate non-linear specifications such as equation (4.24) using $1 - E(U|\varepsilon)$. But as Battese and Coelli (1988) point out, "[t]he expression $1 - U$ includes only the first term in the power-series expansion of exp(-U). The remainder term may be significant when the firm effect U is not close to zero" (p. 390). For this reason equation (4.25) is used to estimate individual efficiency[21].

4.4 Modelling Managerial Efficiency

Having obtained individual efficiency scores for each manager we then need to evaluate these scores. To date most of the studies that have attempted to analyse the determinants of efficiency seem to do so in an ad hoc manner. In contrast our approach is to link explicitly agency theory and human capital theory to managerial performance. In this regard, the question we seek to address is how do incentives and human capital factors affect managerial performance? The main purpose of the following discussion is to establish a framework for integrating the notions of effort (i.e., incentives) and ability (i.e., human capital) in a model of managerial performance.

An agency relationship exists when an owner (principal) employs a manager (agent) to undertake decisions on his/her behalf[22]. The standard agency problem is that the owner requires the manager to maximise performance from a given set of resources. Typically, the manager possesses better information than the owner about production so the owner has to design incentives that will induce the manager to maximise effort

[21] This is also how FRONTIER 4.1 proceeds to estimate individual efficiency (see Chapter 5 for details).
[22] See Chapter 1 for details.

(output) otherwise the manager shirks. For the individual football club the principals are the club shareholders and directors and the agent is the team manager who is hired by the club directors[23].

Following the analysis of Chapter 1, the (football) manager is assumed to be risk-averse and has utility function defined by:

$$M = M(S(w_o)) - \phi(e) \qquad (4.26)$$

and

$$S' > 0; S'' < 0; \phi' > 0; \phi'' > 0.$$

where M is utility; S is the utility of (own) wage w_o; and ϕ the disutility of effort e such that the disutility from effort increases at an increasing rate.

Equation (4.26) states that the manager wishes to maximise his payoff (his wage) and minimise his effort. For simplicity, and following Shapiro and Stiglitz (1984), we assume that the manager either works, e (where $e>0$), or shirks ($e=0$) in a two-period model[24]. The effort decision of the manager is as follows. If the manager works in both periods his wage is $2(S(w_o))$. If he shirks he gets paid $S(w_o)$ in period one. Remuneration in period two depends on the probability of being detected (c), but also on the probability of being fired (f) if caught shirking.

[23] This is not to say that this is the only agency relationship which exists in football. Similar arguments could be made for relationships between managers and players, clubs and supporters, owners and league organisations. Somewhat controversially, McMaster (1997) argues that it is difficult to establish an agency framework in professional football because of the problems in determining ownership and control.

[24] Discounting due to inflation and interest rates is ignored.

The problem for the club owner is designing incentives that will induce the manager to exert maximum effort[25]. Let M^s represent the amount of utility gained by shirking (e.g., in terms of leisure value) and M^{ns} the utility from not shirking. The manager will choose not to shirk if:

$$EU(M^{ns}) \geq EU(M^{s}) \tag{4.27}$$

where EU is expected utility.

The manager's shirking decision can be expressed as:

$$M^{s} > c(w_o - \overline{w})f \tag{4.28}$$

where $c = c\,(\varsigma)$ and $f = f\,(r,\,t)$.

Equation (4.28)[26] states that the effort level of the manager depends on the probability of being detected (c) and the probability of being fired (f) if caught shirking. The probability of detection increases as the level of monitoring (ς) increases. The probability of being fired depends on the availability of a suitable replacement (r) and the total time remaining on the current contract (t). As before, w_o represents the manager's own wage and $\overline{w}$ is the wage in the next best alternative employment (net of search costs). If the probability of finding alternative employment (d) is zero then the wage in next best alternative employment equals the unemployment wage ($\overline{w} = b$). Whereas it

[25] Unfortunately, the nature of the contract for football managers cannot be established because individual wage data for managers is not available.
[26] At the margin (providing EU is positive) we assume the manager strictly prefers to exert a little bit of effort than no effort at all.

equals the reference group wage (i.e., wage of other football managers) if the probability of finding a similar job in the same industry is one ($\overline{w} = w_r$).

The implications of equation (4.28) are as follows. If the level of monitoring is zero, so that the probability of being caught shirking is zero, or the probability of being fired is zero, the manager will maximise his expected utility by shirking. In other words, because the right-hand side of the expression is zero when either c or f is zero there is no explicit cost to the manager in shirking[27]. The manager may even continue to shirk when (perfectly) monitored if he can obtain another job for the same level of utility with certainty[28].

In addition to using monitoring or the threat of dismissal as work incentives, the owner may also use wage incentives. Re-arranging equation (4.28) we have:

$$w_o = \bar{w} + M^s / cf \qquad (4.29)^{29}$$

[27] This assumes that job separation does not occur for non-shirking reasons. If job separation for extraneous reasons could occur equation (4.28) would become:

$$M^s > (c+f)(w_o - \bar{w})$$

[28] This assumes the manager has no concern about his reputation.
[29] Also:

$$c = \frac{M^s}{(w_o - \overline{w})f}$$

and

$$f = \frac{M^s}{(w_0 - \overline{w})c}$$

The critical (effort inducing) wage is inversely related to the level of monitoring and dismissal and positively related to the utility derived from shirking and the wage in the next best alternative employment. The wage here is based on the level of pay (i.e., an efficiency wage). Alternatively it could be based on the nature of the pay, w_i (i.e., incentive payments such as bonuses, piece rates, share options and so on), or the reference wage of other managers who do a similar job in the industry[30].

Overall, managerial effort depends on several factors. Formally:

$$e^M = e^M(c, f, d, b, w_o, w_i, \overline{w}) \tag{4.30}$$

Managerial effort will be greater: the higher the remuneration and the higher the ratio of incentive pay to total remuneration; the larger the difference between the remuneration paid and the next best alternative wage (either the reference wage or unemployment wage) which depends on the probability of re-employment; the higher the level of direct monitoring; and the larger the number of potential replacements.

As the production process (the game) is observed in professional football, the extent to which there are information asymmetries between the club owner and the team manager is likely to be less than that experienced in other sectors of the economy. This is because the owner observes not only the outcome but also the process from which the outcome is derived. In football, unlike other industries, monitoring is relatively costless and also very informative. Furthermore, the short term nature of contracts and the high rate of managerial turnover are also likely to produce high levels of effort. Audas *et al.*

[30] This is based on notions of fairness (morale effects). If two managers of equal ability are remunerated differently, the job satisfaction (and effort) of the manager who views himself to be treated less than fairly will be lower.

(2000) find that one-third of clubs change manager each season (see also Tables 3.6 and 3.7) – much higher than the rates of managerial turnover for North American sports. Evidence presented in Chapter 7 suggests that length of tenure is positively related to the division of employment. For example, the average Premier League manager lasts about four seasons, for managers in Division 1 the figure is just above three, whereas managers employed in the lowest divisions (Divisions 2 and 3) can expect to last on average between two and three seasons.

The effort levels of football managers may, however, vary *within* the football industry. Firstly, monitoring is still far from perfect because the manager may possess information that is not available to the owner. For example, the club owner may not know the true abilities of the playing inputs or the characteristics of the manager that promote success. The manager may be better able to assess the potential (unrealised) talent (true ability) of a promising young player. If this information is not shared with the owner then the owner may incorrectly associate above average performance by this player with managerial performance. Essentially the owner (or owners) has to decide whether the sub-optimal performance of the team is the result of under-performance by individual players, by the manager or the result of purely random factors[31]. Also asymmetries may widen if there are many owners. In such circumstances the level and effectiveness of monitoring will be negatively related to the size of the club.

Given the above, the effort levels of managers may vary further because different clubs have different policies on payment and turnover. Some clubs favour incentive pay, others change their manager more frequently. Most significantly, managers whose

[31] One argument is that the owner hires the manager to eliminate sub-optimal performances by the players. The high rate of managerial turnover would suggest that owners see managers as responsible for player performance.

contracts are terminated with one club often find a comparable position with another club relatively quickly. This is analogous to assuming the probability of being fired is close to zero in equation (4.28).

In Chapter 7 we introduce three variables which can be considered to approximate some of the effort variables in equation (4.30). Unfortunately the manager's wage is not directly observable. However, the club's overall wage bill (see equation (4.5)) relative to the wage bill for "average" club in the division could indicate the use of incentive pay in determining managerial pay (performance-related or efficiency wage)[32]. Secondly, the size of the club (as measured by number of employees) is included to test the proposition that managers at bigger clubs have a greater incentive to shirk. Finally, the club's history of managerial turnover may also influence effort. For example some clubs may actually tolerate some degree of managerial shirking because there may be high turnover costs or a lack of adequate replacements.

Effort is not the only factor which determines managerial performance. Random factors also contribute to performance, so:

$$P^M = P^M(e^M, \theta) \tag{4.31}$$

In part, the random variable (θ) could be influenced by the manager's ability to do the job[33]. The (human capital) quality of the football manager is determined by innate ability (a_i) and ability acquired through labour market experience (a_j). In turn, innate ability is a positive function of leadership (l_i) and motivation (k_i) skills and other non-measurable

[32] Realistically it is more likely to indicate the use of incentive pay for the players.

characteristics. In addition it is possible that these skills can also be acquired (hence, l_j and k_j). These and other human capital attributes are acquired through general labour market training and experience (g_j) and specific labour market training and experience, or job tenure (s_j). Formally:

$$q^M = q^M (a_i, a_j), \tag{4.32}$$

where q^M is the (human capital) quality of the manager, $a_i = a_i (l_i, k_i)$ and $a_j = a_j (g_j, s_j, l_j, k_j)$.

It is likely that all of the attributes in equation (4.32) are positively related to performance and some may be quadratic. In contrast to the dearth of data available to measure managerial effort, there is a greater amount of data regarding the manager's human capital. In Chapter 7 we outline human capital aspects relating to the manager's playing career (quality and quantity) and managerial career to date (general and specific). Substituting equation (4.32) into equation (4.31) yields:

$$P^M = P^M (e^M, q^M, \theta) \tag{4.33}$$

Figure 4.2 illustrates the way in which performance is related to managerial effort and quality. Because the manager derives disutility from effort, then as he exerts more effort his total utility will fall (his disutility is increasing - see equation (4.26)), *ceteris paribus*. As a result he has an upward-sloping marginal cost of effort curve (MCE)[34]. Consider two managers (G and H). Both managers have upward sloping MCE curves,

[33] Even though the owner has full information on the characteristics of the manager, hidden information exists because the owner does not know how these characteristics contribute to performance. The policy

but manager H has a flatter cost of effort curve (MCE_H) because manager H is more able than manager G (either because manager H has a greater stock of innate ability or has undertaken more human capital investment)[35]. If we assume e_2 is the same for both managers, manager G produces performance P_1 and manager H produces performance P_3. Thus by matching the effort level of manager G, manager H will always generate a higher level of performance. For both managers to produce the same level of performance (say P_2), manager H would have to exert effort level e_1 with manager G exerting effort e_3. Thus, manager H can match the improvement in performance made by manager G for a smaller increase in effort. Clearly better managers produce better performance (lower effort) for the same effort (performance) level[36].

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implications derived from this study will help assist owners' hiring decisions.

[34] Overall utility, however, may rise if incentive pay is used to induce effort.

[35] The MCE curves for the two managers do not have the same slope because manager H has greater ability. He can generate the same increment in performance for less effort.

[36] Generally:

$$\frac{\Delta P_H}{\Delta e_H} > \frac{\Delta P_G}{\Delta e_G} \text{ where } \Delta e_G = \Delta e_H$$

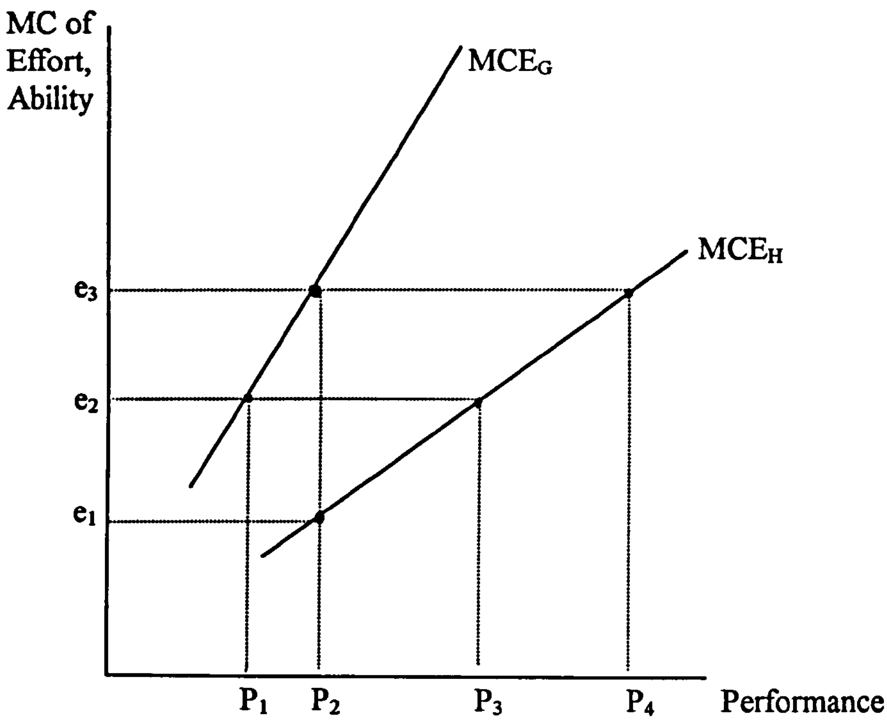
and

$$\frac{\Delta P_H}{\Delta e_H} < \frac{\Delta P_G}{\Delta e_G} \text{ where } \Delta P_G = \Delta P_H$$

providing

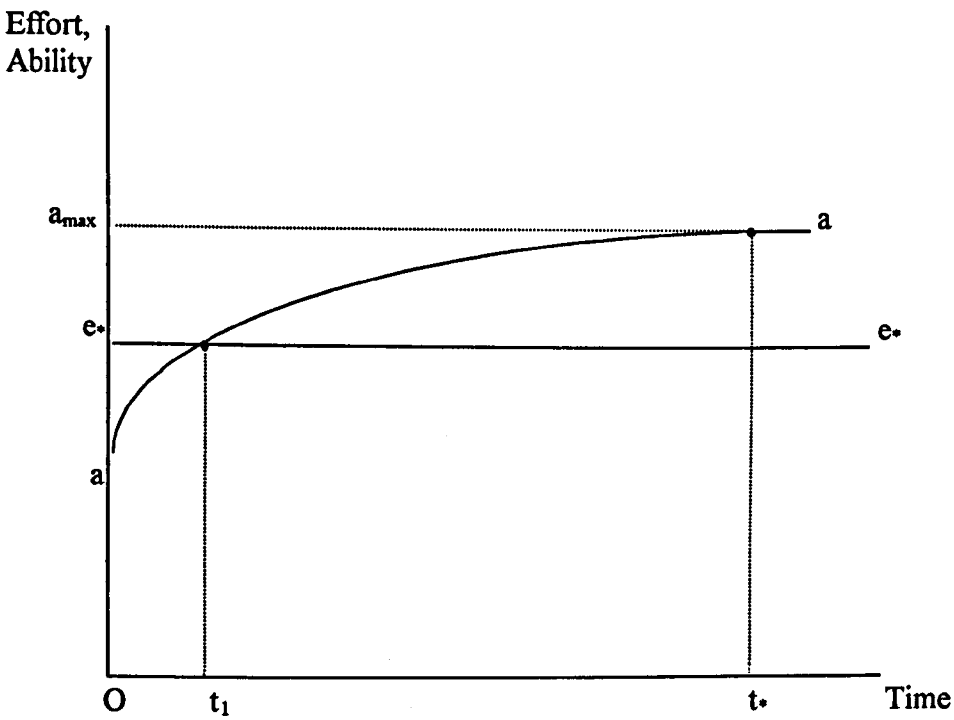
$$q_H > q_G.$$

Figure 4.2 Managerial Effort, Ability and Performance



In order to isolate the impact of human capital from effort over time we reconsider one of the hypothetical managers outlined above (manager G) and assume that he remains with the same club throughout his managerial career. We also assume that the characteristics of the club, in terms of size and ownership structure and number of potential replacements, also remain the same over time. This enables us to assume managerial effort is constant over time. The only aspect that we allow to vary is manager G's human capital investments. The intuition behind this idea is illustrated in Figure 4.3. Manager G's effort level is constant, denoted by the horizontal line e_*e_*. Since almost all football managers have previously been players, managers bring to the job a certain amount of innate ability (e.g., knowledge of the game). For manager G we assume he has innate ability equal to Oa . Over time, manager G gains experience (both general and specific) represented by the concave function aa, representing human capital investment. Therefore, ability increases at a decreasing rate. At time t_1, $e_* = a$. The point at which the two curves intersect will be determined by the current effort-inducing characteristics of the club and the industry (i.e., employment prospects, ownership structure and so on) which influences the position (but not the shape since we assume such characteristics are fixed) of e_*e_*. For example, if effort-inducing characteristics are high, e_*e_* will shift up and the intersection point will move to the right of t_1. Whereas if monitoring is problematic (e.g., many owners) and/or re-employment prospects if fired are high, the point of intersection will move to the left of t_1. Together effort and ability determine the performance, or efficiency, of the manager. The efficiency level of manager G is maximised at a_{max}. This coincides with time t_*.

Figure 4.3 Managerial Effort and Ability over Career Life Cycle



The above framework is necessarily restrictive; it applies to one manager at one club. Different managers will reach a_{max} at different speeds and different times – the function aa will be more (less) concave. For example, managers with more innate ability or who make greater investments in human capital are likely to approach t_* more quickly. Moreover, a turning point may occur each time the manager moves to a different club such that the manager has to incur a reduction in performance whilst he gets established at a new club. The effort function may also be different for different managers. Or it may be different for the same manager over time. It may also be discontinuous, exhibiting a fluctuating step-function as employment conditions at one club change or the manager moves to another club with different employment policies.

Overall, the model suggests that managerial performance is influenced by both effort and human capital factors. Substituting ME_{it} for P^M in equation (4.33), the linear specification for the evaluation of managerial efficiency is given by:

$$ME_{it} = e_{it}^{M}\delta + q_{it}^{M}\delta \tag{4.34}$$

where δ is a vector of coefficients to be estimated.

4.5 Summary

In this chapter we have developed a model of football team production. The use of the production frontier approach requires accurate measurement of the non-managerial inputs in the production process. In professional football, at present, there are two potential measures available that can be used to approximate unobserved player performance. The predicted player transfer value is our preferred measure but wages is useful for purposes of comparison.

The theory behind the ML approach to stochastic frontier analysis was also outlined for the purpose of generating managerial efficiency scores. We continue to use this method for illustrative purposes in Chapter 5. In Chapter 6 we will test statistically whether ML is preferred to fixed effect and random effect panel data models.

Finally, we considered how to analyse the determinants of efficiency. Managerial performance is hypothesised to be influenced by effort (incentives) and human capital factors. While the effort level of the football manager is likely to be high (i.e., the level of incentives required to induce performance compared to other sectors is likely to be less) it may vary across managers because clubs differ in terms of size, payment structures and policy on turnover. Since managers differ according to the level of innate ability and labour market experience (as a player and as a manager) we would expect (human capital) quality to also vary. In Chapter 7 we aim to analyse the importance of human capital and incentives in accounting for variations across managers.

In the next chapter we describe the nature of the data used and the empirical methodology. In particular, we explain how we measure team quality and provide more details as to how this is used to generate estimates of efficiency using a production frontier.

CHAPTER 5

DATA AND METHODOLOGY

5.1 Introduction

In Chapter 4 we discussed the process of modelling football production and managerial efficiency. In this chapter we describe the data sources and the construction of the data used in estimating the production frontier and deriving the managerial efficiency scores. The data set comprises observations on the characteristics of the players and all permanent managerial spells, covering the seasons 1992/93 through to 1997/98. Only a small number of seasons are covered because an extremely large amount of data had to be collected. It is therefore not possible to evaluate managers' performance throughout their career length. Nevertheless we are confident that the sample period is sufficiently long to test several key propositions. We start with season 1992/93 because it coincides with the most recent re-organisation of English football – the inception of the Premier League.

As mentioned in Chapter 2, in order to accurately measure managerial performance using the frontier approach we require an accurate measure of the quality of the playing resources available to the manager. Player quality is determined using a predicted player transfer valuation (SOCCER TRANSFERS). We argued in Chapter 4 that we believe this measure is a suitable proxy for the player's "true" productivity (see also Appendix II). Another approach is to use recorded wage information. However, we firmly believe that such a measure is less robust theoretically and empirically owing to the way the data is compiled. As a result, most of the attention is given to the determination of the transfer values generated by the SOCCER TRANSFERS program[1].

In the final section of this chapter we outline the maximum likelihood estimation procedure following on from the discussions of Chapter 4. Also included is an example of the output results provided by FRONTIER 4.1 based on a simplified version of the stochastic production frontier using our football parameters.

5.2 Data Sources

The principal source of data on clubs and players is contained in Rothmans Football Yearbook which has been published annually since 1971. The Yearbook gives detailed information on team performance in both league (match-by-match) and cup competitions and biographical details of clubs and players. Other useful sources include Playfair Football Who's Who (Rollin, (1997), (1998); formerly Soccer Who's Who, also compiled by Rollin) and Hugman's Football League Players' Records (1992).

An important preliminary source for details on managers is Turner and White (1993). Turner and White present biographical information - playing and managerial careers - of all individuals who managed league clubs from the post-war era to season 1992/93 as well as detailing the month and year in which the appointment started and

[1] As mentioned in Chapter 4, even though we do not have much faith in the reliability of wage data in a production frontier estimation it gives us a way of comparing the results using different input measures.

finished. For managerial careers which commenced after the 1992/93 season data was obtained from a variety of sources (e.g., Electronic Telegraph, Internet sites of individual clubs and up-to-date editions of the Rothmans Football Yearbook).

Finally, financial data is provided by Deloitte and Touche's Annual Review of Football Finance (1996, 1997 and 1998; formerly Touche Ross' Survey of Football Accounts) which records data on turnover, profits, and transfer and wage expenditure from the company accounts of individual clubs.

5.3 Estimation Procedure

In this section we present the methodology behind obtaining managerial efficiency scores. Firstly, we need to estimate individual player quality. We then use these measures to generate a measure of team quality. Finally, we use the measure of team quality together with team performance data to obtain the efficiency of the manager.

5.3.1 Estimating Player Quality

At the start of the 1997/98 football season over 2,200 players were registered with the 92 professional football clubs. However, some of these players will play only a handful of games due to competition for the limited number of places and enforced absence through injury or suspension. To account for this, predicted valuations are only recorded for those players who are considered to have had a significant effect on the team's output. Players that only play a handful of games are unlikely to influence the overall (seasonally adjusted) output measure. Thus, we have arbitrarily chosen a minimum requirement of 25 per cent of all league games available. Based on the 1997/98 season, this translates into 10 games for a player with a Premier League club and 12 games for players playing in the Football League. For the 1997/98 season alone it was necessary to collect 12 pieces of information on 1,683 players. For the six seasons covered in this study we generated a total sample size of 9,786 player observations which amounts to 117,432 separate pieces of information[2].

The SOCCER TRANSFERS program generates a predicted valuation for each player[3]. The program estimates a player's value using a combination of the player's characteristics (age, league record in current and previous seasons and international appearances) and (potential) selling club and buying club characteristics. A complete list of all the variables used in the program is contained in Table 5.1.

[2] This figure includes repeat observations on players over time or in the same season.

[3] Appendix I presents information on the reliability of the predicted player valuations.

Table 5.1 Player Characteristics

Variable	Definition
PLAYER	Those players that played in a minimum of 25 per cent of the matches for the club for the season in question. This measure includes appearances made as a substitute.
LEAGTOT	Total (career) league appearances made by each player. This includes appearances made overseas where available. Another measure considered was total league experience by division (including Scottish and overseas experience).
GLSTOT	Total (career) goals scored by each player (league only). Includes goals scored overseas where available.
PREVCLUB	Number of previous clubs that the player has played for. If a player is contracted to a particular club but makes no appearances for the club it is still counted as a previous club. This measure therefore relates to the number of clubs – temporary and permanent - the player has previously been registered to.
FULLCAPS (CAPS)	Number of full international appearances (including substitute appearances). Between 1992 and 1998, players from a total of 49 different countries have played in English football.
U21CAPS (U21)	Number of U21 caps gained by the player. The data here is restricted to England, Scotland and Wales as these are the only nations where listings are available.
CURRENT: CAPS (t-2) and U21 (t-2)	These two variables measure the extent to which the player is a current (regular) international. If the player has made any international appearances, competitive rather than friendly matches, during the last two seasons (t-2) he is considered a current international.
AGET	Age of the player in years and months (Aug = 0, Sept = 0.917, Oct = 0.833, Nov = 0.75 and so on). For example, the age of a player in born in September 1966 is recorded as 33.917 for August 1999.
TOTLGT	Total league appearances (t-1). Includes both starting and substitute appearances.
STRT	Total number of starting appearances (t-1).
GLST	Total number of goals scored (t-1).
LRDIVT	Divisional status of last registered club (t-1): 1-4 refer to Premier League, Division 1, 2 and 3 respectively. If player played in Scottish Premier League he is given a coding of 1, likewise if he played first-team football overseas. If the player was either a trainee with no club affiliation or played non-league football he is given a coding of 5.
ATTEND	Average attendance of the club the player was last registered to.

The program offers a number of alternative valuation models. The valuation models considered are classified in Table 5.2 and the corresponding correlation matrix is listed in Table 5.3. Based on the predicted individual valuations for season 1997/98 all nine valuations are highly correlated. The lowest correlation is 0.968 (between VALUE 3 and VALUE 4 and between VALUE 3 and VALUE 5). The majority of the other correlations exceed 0.98.

Table 5.2 Predicted Player Valuations: Models Considered

Valuation	Definition
VALUE 1	Baseline valuation[a]
VALUE 2	VALUE 1 incorporating divisional status
VALUE 3	VALUE 1 plus divisional distribution of league experience[b]
VALUE 4	VALUE 1 plus current international effect
VALUE 5	VALUE 1 plus current European / S. American international
VALUE 6	VALUE 1 plus divisional status and current international
VALUE 7	Incorporates aspects relating to VALUE 2 and VALUE 5
VALUE 8	Incorporates aspects of VALUE 3 and VALUE 4
VALUE 9	Incorporates aspects of VALUE 3 and VALUE 5

[a] baseline valuation is based on the following linear equation:
$VALUE\ 1 = \beta_0 + \beta_1 LEAGTOT_{it} + \beta_2 GLSTOT_{it} + \beta_3 PREVCLUB_{it} + \beta_4 AGET_{it} + \beta_5 TOTLGT_{it} + \beta_6 GLST_{it} + V_{it}$
where *LEAGTOT* and *GLSTOT* are career league appearances and career goals; *PREVCLUB* is the number of previous clubs played for (including loan spells); *AGET* is the player's age in years and months; *TOTLGT* and *GLST* relate to current league appearances (t-1) and current league goals (t-1). For each of the valuations the selling club is assumed to be a mid-division team based on player's divisional status and the buying club is a mid-division team based on position and average gate. For a fuller description of each variable see Table 5.1.
[b] It is not possible to incorporate both divisional status (t-1) and divisional distribution of league experience simultaneously.

Table 5.3 Predicted Player Valuations: Correlation Matrix

VALUE	1	2	3	4	5	6	7	8	9
1	1.000								
2	0.981	1.000							
3	0.970	0.981	1.000						
4	0.999	0.979	0.968	1.000					
5	0.999	0.979	0.968	1.000[a]	1.000				
6	0.980	0.999	0.980	0.981	0.980	1.000			
7	0.980	0.998	0.979	0.981	0.981	1.000[a]	1.000		
8	0.969	0.979	0.999	0.970	0.969	0.981	0.980	1.000	
9	0.969	0.979	0.998	0.969	0.969	0.981	0.981	1.000[a]	1.000

Notes: Based on 1997/98 valuations (Aug. 1996 prices). Sample size = 1,683.
[a] Approximately equal to.

We decided to use VALUE 6 when the sample includes only Premier League observations as it includes both divisional status and current international effects. For the "full" (Premier League plus Football League) set of observations we prefer VALUE 2 because the current international effect is likely to be insignificant when comparing divisions.

5.3.2 Estimating Team Quality

In order to obtain a single team valuation measure the individual player valuations are aggregated and then averaged. Taking the average is necessary because of the unequal number of players conforming to the appearance criteria across teams. We did consider aggregating the predicted values for a consistent number of players. For example, the 12 players making the most appearances and the twelve highest valued players). And we looked at ways of classifying playing inputs into defensive and attacking positions (see Table 5.4). But the results were almost identical to the total average measure (TVAV). As Table 5.4 notes all the team valuations used in the regressions have been normalised by the mean value by league for each year.

Table 5.4 A Comparison of Alternative Team Aggregation Methods (All Divisions, Season 1996/97)

Summary Statistics and Selected Regression Variables	Aggregation Methods[a] TVAV	DFAV, OFAV	PMG	MAXVAL
Sample mean	0.804	0.805; 0.804	0.803	0.804
Sample standard deviation	0.292	0.332; 0.304	0.293	0.281
Minimum value	0.222	0.158; 0.242	0.224	0.215
Maximum value	1.48	1.628; 1.551	1.56	1.42
Team Quality Coefficient	1.351	1.376[b]	1.363	1.345
Adj. R^2	0.669	0.676	0.671	0.646
N	109	109	109	109

Notes: Summary measures based on mean deviations of VALUE* 2 (1996/97 season) and includes weights to the input and output measures due to mid-season managerial changes. VALUE* 2 is defined as:

$$VALUE_i^* = \frac{VALUE_i}{\left[\frac{1}{n}\left(\sum_i^n VALUE_i\right)\right]}$$

[a] TVAV = total value averaged; DFAV = average defensive valuation; OFAV = average attacking valuation; PMG = total value of 12 players that played the most games; MAXVAL = total value of the 12 players with the highest valuation.
[b] Team quality coefficient = DFAV + OFAV.

Another issue surrounds the timing of the player valuations. Previous research has measured team quality at the end of the season under review. Here we use a prior measure of playing talent based on the player's value at the start of the season under consideration. (Or wage expenditure from current year end, so that for 1997/98 season we use wage information for accounting year end 1997.) Therefore, the aggregated prior input measure is regressed against the ex post output measure.

5.3.3 Estimating Managerial Performance

In the preceding paragraph we said that the valuation of the player is predicted at the start of the season under consideration. We favour this approach because a player's performance and ultimately that of his team can be affected by managerial strategy during the season. If we were to use an ex post team quality measure we are likely to encounter problems of simultaneity as the impact of the manager in enhancing the players performances will be partially contained within this measure (e.g., Chapman and Southwick, 1991). Under our specification, managerial efficiency is evaluated in terms of how well he can turn a given set of playing resources measured at the start of the season under consideration into team victories[4].

All managers are observed in the study, including mid-season starts and terminations[5]. All other studies have eliminated mid-season changes. By including mid-season changes the output and input measures are weighted according to the formula: number of games the manager is in charge divided by the total number of league games. Further, in generating this kind of panel we have to account for the fact that managers may re-appear at another club either in the same season or in different seasons. To overcome this problem we treat each observation as a managerial appointment, so when a manager changes club he gets a new coding.

The summary statistics in Table 5.4 are expressed as mean deviations. Naturally, if all mid-season terminations are eliminated, the sample means for the various aggregation methods will equal one - managers with above average team valuations will be above one, and managers with below average values less than one. This is clearly not the case in Table 5.4 because mid-season changes are included. The mean deviation approach is the preferred classification because the measure is consistent over time.

---

[4] The prior measure treats all players that conformed to the appearance criteria as having played for the team throughout the season. Thus, players that are transferred to the club and transferred to other clubs during the season, and players who become injured and suspended at crucial times are not accounted for directly in the model. We assume these factors occur randomly.

The total number of managerial observations in each of the divisions for each season is given in Table 5.5. The data set is restricted to managers who were in charge for at least ten games in any one season in order to eliminate short spells undertaken by caretaker managers (temporary rather than permanent replacements). Information on the start and end dates of managerial spells were obtained initially from Turner and White (1993), and the more recent spells were extracted from Rothman's Football Yearbook, Electronic Telegraph and various Internet sites. Where no accurate information exists, other than the start/end month, we assume managerial spells started/ended mid-month, so that we will only over or understate the true length of a spell by a maximum of two weeks (approximately, four games).

Table 5.5 demonstrates that the prospect of managerial turnover is highest in Divisions 1 and 3 and lowest in the Premier League and Division 2. The high levels of turnover experienced in Division 1 reflect the increasing costs of failing to gain entry to the lucrative Premier League. The contrasts offered by the other divisions are not as clear. One possible reason for the difference between managerial turnover in the Premier League compared to Division 3 is that no club is relegated to the Premier League and relatively few clubs are promoted from the Conference League into Division 3, in contrast to the numbers promoted and relegated between Divisions 2 and 3. Hence, the threat of dismissal due to recent relegation is not apparent in the Premier League and, equally, the safeguard of recent promotion seldom exists in Division 3 (Audas *et al.*, 1997).

---

[5] For joint managerial positions we use the manager who remained with the club in the long-term.

Table 5.5 Manager Sample Sizes by Division and by Season

	Managerial Observations[a]				
Season	Premier League	Division 1	Division 2	Division 3	TOTAL
1992/93	23	30	27	27	107
1993/94	27	29	28	24	108
1994/95	29	33	27	28	117
1995/96	21	31	30	30	112
1996/97	23	28	26	32	109
1997/98	24	31	26	27[b]	108
TOTAL	147	182	164	168	661

Notes: Premier League = 22 clubs (1992/93, 1993/94, 1994/95), 20 thereafter; Division 1 = 24 clubs throughout; Division 2 – 24 clubs throughout; Division 3 = 22 clubs (1992/93, 1993/94, 1994/95), 24 thereafter.
[a] Refers to changes which took place during the football season (as opposed to during the close season), providing the outgoing and incoming managers were in charge for a minimum of 10 games in the season in question.
[b] No information available for the manager of one club (Walsall).

The Data Appendix provides a complete list of all the managerial observations in club order by season. Also included are the predicted team quality valuations and team performance data that are used to estimate the stochastic production frontier.

Maximum Likelihood Estimation of a Stochastic Production Frontier

We are now in a position to derive the managerial efficiency scores. In this section we provide a more detailed account of estimating a stochastic production frontier using maximum likelihood (ML) methods. This follows on from the discussions of Chapter 4. The purpose here is to outline a rather simple (restricted) version of a stochastic production frontier and to provide an example of the output results obtained from the computer program FRONTIER 4.1 (Coelli, 1996a) which has been specifically designed to estimate a variety of stochastic frontier models[6].

[6] See Chapters 6 for an empirical investigation of time-invariant and time-varying panel models.

The ML method is also automated in the LIMDEP econometrics program (Greene, 1992)[7]. Both FRONTIER 4.1 and LIMDEP can estimate half-normal and truncated (at zero) normal inefficiency distributions, although only LIMDEP accommodates exponential distributions. With panel data, LIMDEP can estimate balanced or unbalanced random effects models whilst FRONTIER 4.1 estimates the time-varying specification of Battese and Coelli (1992) and the inefficiency effects model (Battese and Coelli, 1995) for either balanced or unbalanced panels[8].

The two programs differ in their re-parameterisation of equation (4.18). FRONTIER 4.1 follows the parameterisation of Battese and Corra (1977) who replace σ_V^2, σ_U^2 with:

$$\sigma^2 = \sigma_U^2 + \sigma_V^2 \quad (5.1)$$

and

$$\gamma = \frac{\sigma_U^2}{\sigma_U^2 + \sigma_V^2} \quad (5.2)$$

LIMDEP uses $\sigma^2 = \sigma_U^2 + \sigma_V^2$ and $\lambda = \frac{\sigma_U}{\sigma_V}$ as outlined in Aigner *et al.* (1977). One of the benefits of using FRONTIER 4.1 is that the gamma variance parameter in equation (5.2) has a finite value range (between zero and one). At the limit, if gamma is one then the deviation from the production frontier is due entirely to inefficiency, whereas if gamma is zero the deviation is entirely the result of statistical noise. The equivalent parameter in LIMDEP (i.e., lambda) has an infinite range. The finite range allows us to

[7] Econometric packages such as GAUSS and SAS can also be used to estimate frontier models if the analyst is familiar with computer programming.

determine a good starting value for the maximum likelihood estimation procedure, although Sena (1999) finds that the two programs produce identical production parameter and efficiency estimates[9]. Even so, FRONTIER 4.1 is the preferred program because it considers a greater number of model variants.

In order to facilitate the ML procedure the appropriate log-likelihood function needs to be formed. Using equations (5.1) and (5.2), and incorporating these into the density function for Y (i.e., equation (4.18)) gives the following log-likelihood function:

$$L(\vartheta^*;Y) = -\frac{n}{2}\ln\sigma^2 - \frac{n}{2}\ln 2\pi - \frac{1}{2\sigma^2}\sum^{n}\left(Y - \beta_0 - \beta_1 Q^T\right)^2 + \sum^{n}\ln\left[1-\Phi(z_*)\right] \qquad (5.3)$$

where $z_* = \left[\left(Y - \beta_0 - \beta_1 Q^T\right)/\sigma\right]\left[\gamma/(1-\gamma)\right]^{1/2}$ and $\vartheta^* = \left(\beta_0, \beta_1, \sigma^2, \gamma\right)$.

The first-order partial derivatives of the log-likelihood function with respect to the parameters β_0, β_1, σ^2, γ are defined as:

$$\frac{\delta L}{\delta\beta_0} = \sigma_* \sum \frac{\phi(z_*)}{1-\Phi(z_*)} + \left[\frac{1-\gamma)}{\gamma\sigma^2}\right]^{1/2} \sum z_* = 0 \qquad (5.4)$$

$$\frac{\delta L}{\delta\beta_1} = \sigma_* \sum \frac{\phi(z_*)}{1-\Phi(z_*)} Q^T + \left[\frac{1-\gamma)}{\gamma\sigma^2}\right]^{1/2} \sum z_* Q^T = 0 \qquad (5.5)$$

$$\frac{\delta L}{\delta\sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^2}\sum \frac{\phi(z_*)}{1-\Phi(z_*)} z_* + \frac{1-\gamma}{2\gamma\sigma^2}\sum z_*^2 \qquad (5.6)$$

---

[8] See equations (2.18) and (2.20) and Chapter 6 for further details on these models.

[9] Even though the gamma parameter is preferred it cannot be directly interpreted as the ratio of variance of inefficiency to the composed residual. It has been shown (e.g., Battese and Corra, 1977) that the variance of inefficiency is actually $\text{Var}(U) = \left(\frac{\pi - 2}{\pi}\right)\sigma_U^2$. Therefore: $\gamma^* = \frac{(\pi - 2/\pi)\sigma_U^2}{(\pi - 2/\pi)\sigma_U^2 + \sigma_V^2}$.

$$\frac{\delta L}{\delta \gamma} = -\frac{1}{2}\left[\frac{1}{\gamma(1-\gamma)}\right]\sum \frac{\phi(z_*)}{1-\Phi(z_*)} z_* \tag{5.7}$$

Unfortunately the first-order partial derivatives cannot be easily calculated. Approximations to the parameter estimates can however be achieved using numerical unconstrained optimisation techniques.

The concept of multi-variable maximisation in n-dimensional Euclidean space is usually approximated by a Taylor series expansion. Assuming that the function is continuous and differentiable equation (5.3) can be expressed as:

$$f(\vartheta + \Delta\vartheta) = f(\vartheta) + f'(\vartheta)\Delta\vartheta + \frac{(\Delta\vartheta)^2}{2} f''(\vartheta) + \ldots \tag{5.8}$$

or in matrix form:

$$f(\vartheta + \Delta\vartheta) = f(\vartheta) + J^T \Delta\vartheta + \frac{\Delta\vartheta^T}{2} H \Delta\vartheta + \ldots \tag{5.9}$$

In both equation (5.8) and equation (5.9), $f(\cdot)$ represents the objective function (in this case a maximum production function) and ϑ represents the parameters in the log-likelihood function. In equation (5.9) J^T is the transpose of the Jacobian (gradient) vector of first order partial derivatives and H is the Hessian matrix of second-order derivatives.

At the maximum, first-order derivatives ($\beta_0, \beta_1, \sigma,^2 \gamma$) will equal zero (a necessary condition for a maximum) and the second order derivatives are negative definite (sufficient condition for a maximum). When these derivatives cannot be solved easily, as in equations (5.4) - (5.7), numerical methods are used. Numerical methods can be categorised into search methods and gradient methods. Search methods evaluate the functional values of ϑ. Gradient methods, as the name suggests, evaluate both the values of ϑ and the partial derivatives of ϑ. Since the concern here is to determine the partial derivatives of the log-likelihood function, analysis focuses exclusively on these gradient techniques[10].

Gradient methods are based on the Taylor series expansion (i.e. as in equation (5.8) and (5.9)). There are two types: first-order methods and second-order methods. Second-order methods, such as the Newton-Raphson method, give better results but they require information about the Hessian matrix[11]. This may not be a problem as long as the function is, say, quadratic but for more complex functions it becomes more problematic and convergence to the maximum point is not always possible. If the matrix is not negative definite divergence could occur (this is particularly true if the starting value is some way from the maximum point). In addition, there may be computational costs in evaluating the inverse of the Hessian matrix during each step of the iterative process.

---

[10] A number of multi-dimensional search methods are available. Among the most popular are Nelder and Mead's simplex method and the direction-set method (see Press *et al.*, 1986, for details).
[11] The inverse of the Hessian matrix is found as follows:

$$J + H\Delta\vartheta = 0$$

which implies

$$J = -H\Delta\vartheta$$

and

$$\Delta\vartheta = -H^{-1}J$$

Given that convergence may not be achieved and evaluation of second-order derivatives may be costly, approximations to a negative definite matrix are generally used instead. Gradient methods using this approach are termed quasi-Newton (or variable metric) methods. These methods use an initial estimate of the inverted Hessian matrix, such as the identity matrix, and then continuous iterations update it on the basis of the information obtained from the changes in the Jacobian gradient vector. At the maximum point the estimated Hessian inverse matrix should approximate the 'true' Hessian inverse matrix, unless the routine terminates after only a few iterations. This is how the Davidon-Fletcher-Powell (DFP) method proceeds.

Example Using The Computer Program FRONTIER 4.1

This section contains an example of the standard stochastic production frontier model that can be estimated by the computer program FRONTIER 4.1. To illustrate the estimation of a stochastic production frontier we assume a Cobb-Douglas function form, which when transformed into natural logarithms is specified as:

$$\ln Y_i = \ln \beta_0 + \ln \beta_1 PV_i^T + V_i - U_i \qquad (5.10)$$

where variables are as defined in equation (4.8) and the subscript i represents the i-th manager. The data is a cross-section of 108 football managers employed during the season 1997/98 (file name = AL978.CSV). Given that the data is cross-sectional a specific distribution for the efficiency term is required. For the purposes of the example we assume efficiency has a half-normal distribution (see equations (4.11) and (4.13)).

Table 5.6 lists the output results from the program[12].

Table 5.6 Output File, AL978.OUT

```
Output from the program FRONTIER (Version 4.1c)


instruction file = terminal
data file =        al978.csv

Error Components Frontier (see B&C 1992)
The model is a production function
The dependent variable is logged

the ols estimates are :

                 coefficient     standard-error    t-ratio

  beta 0        -0.10343818E+01  0.41442248E-01 -0.24959596E+02
  beta 1         0.12017069E+01  0.80032980E-01  0.15015147E+02
  sigma-squared  0.13287037E+00

log likelihood function =  -0.43243396E+02

the estimates after the grid search were :

  beta 0        -0.71475586E+00
  beta 1         0.12017069E+01
  sigma-squared  0.23257052E+00
  gamma          0.69000000E+00
  mu is restricted to be zero
  eta is restricted to be zero

iteration =     0  func evals =     19  llf = -0.41599694E+02
    -0.71475586E+00 0.12017069E+01 0.23257052E+00 0.69000000E+00
 gradient step
 iteration =     5  func evals =     62  llf = -0.41140254E+02
    -0.71673417E+00 0.11188519E+01 0.24780445E+00 0.75202621E+00
 iteration =     8  func evals =    121  llf = -0.41140213E+02
    -0.71718370E+00 0.11187817E+01 0.24737674E+00 0.75154170E+00

the final mle estimates are :

                 coefficient     standard-error    t-ratio

  beta 0        -0.71718370E+00  0.64131743E-01 -0.11182975E+02
  beta 1         0.11187817E+01  0.88111596E-01  0.12697327E+02
  sigma-squared  0.24737674E+00  0.58913990E-01  0.41989474E+01
  gamma          0.75154170E+00  0.12868128E+00  0.58403342E+01
  mu is restricted to be zero
  eta is restricted to be zero
```

[12] For a description of the operating procedure see Coelli (1996a).

```
log likelihood function =   -0.41140213E+02

LR test of the one-sided error =    0.42063655E+01
with number of restrictions = 1
[note that this statistic has a mixed chi-square distribution]

number of iterations =      8

(maximum number of iterations set at :   100)

number of cross-sections =    108

number of time periods =     1

total number of observations =    108

thus there are:      0  obsns not in the panel


covariance matrix :

  0.41128804E-02 -0.20768310E-03  0.28347320E-02  0.61460217E-02
 -0.20768310E-03  0.77636533E-02 -0.18360364E-02 -0.51629859E-02
  0.28347320E-02 -0.18360364E-02  0.34708582E-02  0.61639862E-02
  0.61460217E-02 -0.51629859E-02  0.61639862E-02  0.16558873E-01


technical efficiency estimates :

     firm            eff.-est.

       1          0.67515666E+00
       2          0.78811374E+00
       3          0.80625151E+00
       4          0.85035425E+00
       5          0.75993178E+00
       6          0.83182796E+00
       7          0.82081536E+00
       8          0.78558902E+00
       9          0.76259584E+00
      10          0.82035848E+00
```

[technical efficiency estimates of 'firms' 11-99 are deleted to save space]

```
     100          0.67992904E+00
     101          0.48702199E+00
     102          0.73343242E+00
     103          0.91014262E+00
     104          0.83128735E+00
     105          0.75036276E+00
     106          0.68562177E+00
     107          0.79393234E+00
     108          0.72780507E+00

mean efficiency =   0.73452474E+00
```

FRONTIER 4.1 uses initial search routines in order to obtain starting values in the DFP process. The search routine is based, in the first instance, on calculating the OLS estimates, followed by corrections to the intercept term and sigma-squared. The corrections are necessary because the two terms will be biased in the OLS estimation procedure. The corrections are based on the following formulae[13]:

$$\hat{\beta}_0 = \hat{\beta}_{0(OLS)} + \sqrt{\frac{2\hat{\gamma}\hat{\sigma}^2}{\pi}} \tag{5.11}$$

$$\hat{\sigma}^2 = \hat{\sigma}^2_{OLS}\left[\frac{\pi(T-K)}{T(\pi-2\hat{\gamma})}\right] \tag{5.12}$$

Next the gamma parameter is evaluated between zero and one. The values that maximise the log-likelihood from this stage form the starting values in the DFP process (in the above example this was found to be 0.69). As the gamma parameter is evaluated over the entire length of its parameter space (unlike the lambda parameter in LIMDEP), it is reasonable to assume that appropriate ML estimates are obtained. Notice also that mu is restricted to be zero because we assume efficiency is half-normal, eta is zero because we are dealing with cross-section data. The final ML estimates are obtained when the convergence criteria is satisfied. In FRONTIER 4.1 the iterative procedure stops when the proportional change in the likelihood function and each of the parameters is less than 0.00001. Alternatively the iterative procedure terminates if the number of iterations reaches 100. In the above example the convergence criteria was satisfied after eight iterations.

---

[13] Coelli (1995).

The parameter value for team quality (beta one) is close to the OLS value. More importantly, the value of the gamma parameter suggests that much of the variation in the residual is attributable to a lack of efficiency. This is confirmed by the significance of the likelihood ratio test based on the OLS model (i.e., all managers are fully efficient) versus the ML stochastic frontier model[14].

Standard errors (and t-ratios) are obtained from the direction matrix from the final iteration of the DFP procedure. However, if the procedure converges after a few iterations the direction matrix may not be a good approximation to the inverse of the Hessian. If this is the case the standard errors will be inefficient and the direction matrix should not be used for the basis of statistical inference.

Finally, the output file also contains a list of firm (in our case, managerial) efficiency scores (based on equation (4.25)) and the overall average.

5.4 Summary

The data on players and managers was collected from a number of sources. For the six seasons covered in the study we have data on 9,786 players and 319 managerial appointments. We have seen how individual player quality is estimated and how it is used to construct a measure of team quality. Team quality together with team performance is then used in a frontier estimate to predict managerial performance. Here we provided details of the ML technique including the results obtained from FRONTIER 4.1 using a cross-section of managers.

---

[14] This statistic has a mixed distribution so the appropriate hypothesis test is more complicated. See Chapter 6 for details on this.

In the next two chapters the empirical results are reported. In Chapter 6 we address the question of model specification when panel data is available. In particular we are concerned with the way the managerial efficiency scores are influenced by alternative input and output measures and competing estimation procedures. For example, how do the absolute efficiency scores and rankings change when we consider fixed rather than random effects, and how important are the distributional assumptions regarding the efficiency term? Are the efficiency scores time-varying or time-invariant? How do they change when wage data is used instead of predicted player values? And are the results comparable for different sample sizes (e.g., Premier League managers versus Premier League and Football League managers)?

Using the preferred model from Chapter 6, Chapter 7 provides a detailed account of how human capital and effort (incentives) affect managerial efficiency. Questions to be discussed here include whether human capital influences managerial efficiency, or whether it only serves as a signalling device in the job hiring process. Do incentives influence efficiency, and do they matter more or less than the human capital factors?

CHAPTER 6

EMPIRICAL RESULTS I:

SPECIFICATION AND ESTIMATION OF MANAGERIAL EFFICIENCY

6.1 Introduction

Since its inception in 1977 the stochastic production frontier technique has increasingly been used as a way of measuring technical efficiency. Previous studies have almost exclusively examined how the estimation procedure impacts on the reported efficiency scores. Several estimation methods have been considered. For cross-sectional studies we could use corrected ordinary least squares (COLS) or maximum likelihood (ML) estimation. When panel data is available we can use fixed effects (i.e., within estimator), or random effects (i.e., generalised least squares or maximum likelihood estimators)[1]. In addition, efficiency in panel data models can be treated as time-varying or time-invariant.

Many studies have also considered the issue of functional form. The choice between a Cobb-Douglas and translog specification is usually made on empirical grounds. The translog specification is usually favoured even though the parameter estimates are highly co-linear.

---

[1] Recall from Chapter 2 that the focus of this study is stochastic parametric models rather than deterministic parametric and non-parametric models.

In contrast, the choice of alternative input and output measures has received little attention in the empirical literature. We know of no study which has attempted to compare efficiency scores using alternative input and output classifications. A comparison of efficiency levels using different input and output measures is a logical extension because the choice of measure is likely to have just as big an impact on efficiency as both the estimation procedure and choice of functional form. The football industry offers a number of competing input and output measures.

In this chapter, several empirical models are used to generate managerial efficiency estimates for an unbalanced panel of football managers in the Premier League and Football League over the period 1992-1998. Our concerns are twofold. First, we investigate how the efficiency scores are affected by the choice of the estimation procedure and whether efficiency is time-invariant or time-varying. The various models are evaluated in terms of Hausman specification tests, likelihood ratio tests and conventional regression diagnostics. Second, we analyse how the efficiency scores are affected by the choice of input and output measures[2]. We consider predicted player (team) valuation and recorded wage data as alternative input measures; win ratio and points ratio as alternative output measures[3].

[2] A detailed examination of the sources of efficiency is considered in Chapter 7.

[3] As a robustness check we also consider the influence on team output of the variables which determine the predicted transfer valuation.

6.2 Model Specifications

Before presenting the results we briefly re-introduce the basic panel data model[4]. The stochastic frontier production function with panel data is written as:

$$Y_{it} = \beta_0 + \beta_1 Q_{it}^T + \beta_2 TIME + (V_{it} - U_{it}) \qquad (6.1)$$

where Y_{it} denotes a singular measure of output (for team i in season t); Q_{it}^T is a singular measure of team quality (discussed below); $TIME$ is a control variable which takes account of technical progress (or regress); and β_0, β_1, and β_2 are unknown parameters to be estimated. The random term V_{it} is iid $N(0,\sigma_V^2)$ and assumed to be uncorrelated with Q_{it}^T. U_{it} is a non-negative truncated variable which represents managerial efficiency. It is typically taken to be iid $N(0,\sigma_U^2)$[5] or $N(\mu,\sigma_U^2)$[6] and uncorrelated with Q_{it}^T. V_{it} and U_{it} are the residual components; V_{it} represents factors not under the manager's control whereas the one-sided term (U_{it}) represents factors under the manager's control. The residual components are also considered to be uncorrelated.

[4] See Chapters 2 and 4 for more details.
[5] Half-normal distribution.
[6] Truncated-normal distribution.

6.2.1 Estimation Procedure

The basic model in equation (6.1) can be used to estimate efficiency using a number of estimators. These estimators can be classified as fixed effects or random effects. In Section 6.3 four alternative panel data estimators are considered: within estimator, generalised least squares (GLS) and ML under half-normal and truncated-normal distributions[7]. The within estimator is the fixed effects model whereas GLS and ML are random effects models, although only the ML method requires distributional assumptions regarding efficiency. The four models are compared in the context of time-invariant efficiency. The possibility of time-varying efficiency is then considered using the time-varying effects model (Battese and Coelli, 1992) and the inefficiency effects model (Battese and Coelli, 1995).

<u>Within Estimator</u>

The within estimator involves estimating a separate intercept for each manager. OLS is applied once the data is expressed in terms of mean deviations (within transformation). It assumes U_i is fixed for each manager (fixed effects). The within estimator equivalent of equation (6.1) is expressed as:

$$Y_{it} = \alpha_i + \beta_1 Q_{it}^T + \beta_2 TIME + V_{it} \qquad (6.2)$$

[7] The Hausman-Taylor estimator is not considered because generally we have only two explanatory parameters.

where $\alpha_i = \beta_0 - U_i$ and the data is expressed in terms of deviations such that Y_{it} is replaced with $Y_{it} - \overline{Y}_i$ and Q_{it}^T is replaced with $Q_{it}^T - \overline{Q}_i^T$. The intercepts for each manager are recovered as the mean of the residuals for each manager[8]. This is the within transformation method. U_i is found by assuming the largest mean residual value is 100 per cent efficient. Then, individual efficiency of the other managers can be found as deviations from the optimal (best performing) manager:

$$\hat{U}_i = \max(\hat{\alpha}_i) - \hat{\alpha}_i \tag{6.3}$$

The principal advantages of the fixed effect (FE) approach are that it does not require any distributional assumptions regarding U_i and it does not require U_i and Q_{it}^T to be uncorrelated. However, it does ignore cross-sectional variation in managerial efficiency over time. In addition, the estimator only applies to the cross-sectional units in the study. Therefore, the estimator is only appropriate if the sample exhausts the population. The most serious question mark with the FE approach is that it is impossible to include variables that vary across clubs but are time-invariant for the individual club (Schmidt and Sickles, 1984). Omitting these variables from the model is not an option because they will reappear as fixed effects and contaminate the efficiency scores.

[8] Alternatively, OLS is applied to N-1 dummy variables. The within transformation method is the preferred method because it is the one which is most frequently operationalised in the literature. See Chapter 2 for a discussion of the dummy variable approach.

Generalised Least Squares Estimator[9]

Variables that are time-invariant can be accounted for if we are willing to assume U_i is uncorrelated with Q_{it}^{T}. This approach assumes U_i is randomly distributed across cross-sectional units, and hence is known as the random effects (RE) model. The GLS version of the RE requires no distributional assumptions for the efficiency term and can be expressed as:

$$Y_{it}^{*} = \alpha + \beta_1 (Q_{it}^{T})^{*} + \beta_2 TIME + (V_{it} - U_{it}^{*}) \qquad (6.4)$$

where $\alpha = \beta_0 - \mu_i$ and $U_i^{*} = U_i - \mu_i$. The input and output variables are transformed by $Y_{it}^{*} = Y_{it} - \hat{\vartheta}\overline{Y}_i$ and $(Q_{it}^{T})^{*} = Q_{it}^{T} - \hat{\vartheta}\overline{Q}_i^{T}$ where:

$$\vartheta = 1 - \sqrt{\frac{\sigma_V^2}{\left(\sigma_V^2 + T\sigma_\alpha^2\right)}} \qquad (6.5)$$

Residuals from the OLS pooled sample and the within estimator provide unbiased estimates of the variance components in equation (6.5)[10]. The residuals from equation (6.4) can be used to estimate individual intercepts using the mean of the residuals for individual managers over time. As with the within estimator, individual managerial efficiency is recovered using equation (6.3).

For both the within estimator and GLS consistency of the individual intercepts requires the number of time periods to approach infinity ($T \to \infty$) and consistency of the

[9] Specifically it is a feasible GLS estimator because the variance components are unknown.

estimated inputs require either $T \to \infty$ or the number of observations to approach infinity ($N \to \infty$). However, consistency of U_i requires both $T \to \infty$ and $N \to \infty$, whilst if T and N are large GLS is no more efficient than within estimation (see, Schmidt and Sickles, 1984). If T is large (compared to N) it is doubtful whether managerial efficiency remains time-invariant[11].

ML Estimation Methods

The RE model can also be generated using ML techniques. ML is more restricted than GLS because in addition to the zero correlation assumption, distributional assumptions for the efficiency term must be specified. Three types of ML model are considered.

Model 1: Time-Invariant Managerial Efficiency

The first model assumes, as in within estimation and GLS, that managerial efficiency is time-invariant. The log-likelihood function assuming U_i ($= U_{it}$) follows the truncated-normal distribution and V_{it} is normal is given by[12]:

$$\begin{aligned} L(\vartheta^*;Y) = &-\frac{n}{2}T\ln\sigma^2 - \frac{n}{2}T\ln 2\pi - \frac{n}{2}(T-1)\ln(1-\gamma) - \frac{n}{2}\ln[1+(T-1)\gamma] \\ &- n\ln[1-\Phi(-z)] - \frac{n}{2}z^2 + n\ln[1-\Phi(-z_*)] + \frac{n}{2}z_*^2 \\ &- \frac{nT}{2}\frac{\left(Y - \beta_0 - \beta_1 Q^T - \beta_2 TIME + \mu\right)^2}{(1-\gamma)\sigma^2} \end{aligned} \tag{6.6}$$

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[10] A number of computer packages (e.g., Stata, TSP) calculate these automatically.
[11] See Chapter 2 for details.
[12] The following log-likelihood functions are based on the parameterisation of Battese and Corra (1977). See Chapter 5 for details. Chapters 4 and 5 also contain the log-likelihood and formula for estimating

where $z = \frac{\mu}{(\gamma\sigma^2)^{1/2}}$, $z_* = \frac{\mu(1-\gamma) - \gamma T(Y - \beta_0 - \beta_1 Q^T - \beta_2 TIME)}{\{\gamma(1-\gamma)\sigma^2[1+(T-1)\gamma]\}^{1/2}}$ and

$\vartheta^* = (\beta_0, \beta_1, \beta_2, \mu, \sigma^2, \gamma)$.

Individual efficiency is calculated from the conditional probability of U_i given ε_{it} (i.e., $\varepsilon_{it} = V_{it} - U_i$)[13]:

$$E[\exp(-U_i|\varepsilon_i)] = \exp(-\mu_* + \sigma_*^2/2)\left[\frac{1-\Phi(\sigma_* - (\mu_*/\sigma_*))}{1-\Phi(-\mu_*/\sigma_*)}\right] \tag{6.7}$$

where $\mu_* = \frac{(-\sigma_U^2\bar{\varepsilon}_i + \mu\sigma_V^2 T^{-1})}{\sigma_U^2 + \sigma_V^2 T^{-1}}$ and $\sigma_* = \left(\frac{\sigma_U^2\sigma_V^2}{T\sigma_U^2 + \sigma_V^2}\right)$ such that $\bar{\varepsilon}_i$ is defined as

$\bar{\varepsilon}_i = T^{-1}\sum_{t=1}^{T}\hat{\varepsilon}_{it}$.

Model 2: Time-Varying Managerial Efficiency I: Battese and Coelli's 1992 Model

Two other ML efficiency models both formulate managerial efficiency as time-varying, thereby including cross-sectional variation in managerial efficiency over time. The first assumes U_{it} is a deterministic function of time utilising the model specified by Battese and Coelli (1992, BC (1992) hereafter) and is expressed as:

$$U_{it} = (\exp[-\eta(t-T)])U_i \tag{6.8}$$

managerial efficiency under the half-normal distribution. Subscripts are dropped to simplify expressions.

[13] This is the time-invariant equivalent of equation (4.25).

where η is the time-varying parameter which either increases, decreases or remains constant as t increases. If η is constant then managerial efficiency is time-invariant. Thus, time-invariant efficiency is nested within this model and can be tested for using likelihood ratio tests. If η is positive efficiency monotonically increases over time (inefficiency falls), whereas if η is negative efficiency monotonically decreases over time (inefficiency rises). T denotes the last football season in the panel and the season under consideration is denoted by t. Therefore, if a particular manager is observed in the last season $t = T$ and $U_{iT} = U_i$ (since $exp(0) = 1$). In this case efficiency will monotonically rise to this level if η is positive ($U_{iT} > U_i$) and monotonically fall to this level if η is negative ($U_{iT} < U_i$).

Because η is the same for each manager, the ordering of managerial efficiency is preserved in all time periods. For example, if manager G is more efficient than manager H in the opening season, manager G will still be more efficient than manager H in subsequent seasons. This is quite a restrictive assumption because it cannot account for situations where the efficiency of some managers worsens over time and the efficiency of other managers improves over time.

For this model the log-likelihood function is[14]:

$$\begin{aligned} L(\vartheta^{*};Y) = & -\frac{n}{2}T\ln\sigma^{2} - \frac{n}{2}T\ln 2\pi - \frac{n}{2}(T-1)\ln(1-\gamma) - \frac{n}{2}\ln\left[1+(\eta^{2}-1)\gamma\right] \\ & - n\ln\left[1-\Phi(-z)\right] - \frac{n}{2}z^{2} + n\ln\left[1-\Phi(-z_{*})\right] + \frac{n}{2}z_{*}^{2} \\ & - \frac{nT}{2}\frac{\left(Y-\beta_{0}-\beta_{1}Q^{T}-\beta_{2}TIME\right)^{2}}{(1-\gamma)\sigma^{2}} \end{aligned} \qquad (6.9)$$

where z is as defined previously, $z_* = \dfrac{\mu(1-\gamma) - \gamma\eta(Y - \beta_0 - \beta_1 Q^T - \beta_2 TIME)}{\left\{\gamma(1-\gamma)\sigma^2\left[1+(\eta^2-1)\gamma\right]\right\}^{1/2}}$ and

$\vartheta^* = \left(\beta_0, \beta_1, \beta_2, \mu, \eta, \sigma^2, \gamma\right)$.

Individual efficiency is found by applying the formula:

$$E\left[\exp(-U_i|\varepsilon_i)\right] = \exp(-\eta\mu_* + \eta^2\sigma_*^2/2)\left[\frac{1-\Phi(\eta\sigma_* - (\mu_*/\sigma_*))}{1-\Phi(-\mu_*/\sigma_*)}\right] \qquad (6.10)$$

where $\mu_* = \dfrac{\left(-\eta\sigma_U^2\bar{\varepsilon}_i + \mu\sigma_V^2\right)}{\eta^2\sigma_U^2 + \sigma_V^2}$ and $\sigma_* = \left(\dfrac{\sigma_U^2\sigma_V^2}{\eta^2\sigma_U^2 + \sigma_V^2}\right)$.

Model 3: Time-Varying Managerial Efficiency II: Battese and Coelli's 1995 Model

The ML approach is more efficient than the within estimator and the GLS estimator provided the distributional assumptions regarding the efficiency term is correctly specified. One drawback with the ML approach is that in order to analyse the determinants of managerial efficiency, the efficiency scores in the first stage have to form the dependent variable in the second stage[15]. As mentioned in Chapter 2, several authors have criticised this approach (Kumbhakar *et al.* (1991); Reifschneider and Stevenson (1991); and Battese and Coelli (1995)) on the grounds that inconsistencies arise in the second-stage because the first stage efficiency scores are assumed to be identically

[14] Full derivation of the log-likelihood can be found in the appendix of Battese and Coelli (1992).
[15] For the within estimator and GLS this problem does not arise because neither approach requires any specific distributional assumptions for managerial efficiency. However, OLS is not an efficient method for the second stage estimation (see Chapter 2).

distributed. Regressing the efficiency scores on a set of explanatory variables in the second stage implies that they are not identically distributed.

To take account of this problem we adopt a single-stage specification which estimates the production frontier parameters and the inefficiency effects[16] simultaneously. Based on Battese and Coelli (1995, BC (1995) hereafter) efficiency is specified as:

$$U_{it} = Z_{it}\delta + W_{it} \tag{6.11}$$

where W is an independently distributed random factor, is $N(0,\sigma_U^2)$ and is truncated from below: $W_{it} \geq -Z_{it}\delta$. Alternatively, but consistent with equation (6.11), U_{it} is a non-negative truncation (at zero) distributed as $N(Z_{it}\delta, \sigma_U^2)$. In each case, Z is a vector of variables which influence managerial efficiency (or inefficiency), and δ is a vector of unknown coefficients to be estimated. The single-stage estimation means that the sources of efficiency are built directly into the regression. With ML as the estimation procedure, the likelihood function is:

$$L(\vartheta^*;Y) = -\frac{n}{2}T\ln\sigma^2 - \frac{n}{2}T\ln 2\pi - n\ln[1-\Phi(-d)] + n\ln[1-\Phi(-d_*)] - \frac{nT}{2}\frac{\left(Y-\beta_0-\beta_1 Q^T - \beta_2 TIME + Z\delta\right)^2}{\sigma^2} \tag{6.12}$$

where $d = \frac{Z\delta}{(\gamma\sigma^2)^{1/2}}$, $d_* = \frac{\mu_*}{\sigma_*}$, $\mu_* = (1-\gamma)Z\delta - \gamma(Y-\beta_0-\beta_1 Q_{it}^T - \beta_2 TIME)$,

$\sigma_* = \left[\gamma(1-\gamma)\sigma^2\right]^{1/2}$ and $\vartheta^* = \left(\beta_0, \beta_1, \beta_2, \delta_0, \ldots, \delta_n, \sigma^2, \gamma\right)$.

[16] We use the term inefficiency effects because this is generally preferred in the literature and because the δ parameters are treated as inefficiency rather than efficiency determinants.

Individual efficiency is found by applying the formula:

$$E\left[\exp(-U_i|\varepsilon_i)\right] = \exp(-\mu_* + \sigma_*^2/2)\left[\frac{1-\Phi(\sigma_* - (\mu_*/\sigma_*))}{1-\Phi(-\mu_*/\sigma_*)}\right] \qquad (6.13)^{17}$$

The model allows the mean to vary across managers rather than assuming it to be constant for all managers. Thus, it extends the truncated-normal formulation by allowing managerial efficiency to differ across managers. The extent to which managerial efficiency differs depends on the sign and the magnitude of the inefficiency effects (i.e., the δ parameters). If δ_0 is the only inefficiency effect then the model reduces to the truncated-normal constant mean model with log-likelihood and individual efficiency estimated using equation (6.6) and equation (6.7).

As the mean is allowed to vary, the BC (1995) specification is useful in correcting for heteroskedasticity in the one-sided error term (Stevenson and Reifschneider, 1991). The more conventional approach is to correct for heteroskedasticity in the variance of the one-sided error term (e.g. Caudill *et al.*, 1995; Hadri *et al.*, 1999). We adopt the BC (1995) approach because it is automated in FRONTIER 4.1[18].

6.2.2 Input and Output Measurement

As well as the choice of estimation procedure we also consider the choice of input and output measures. In the North American literature, output is conventionally measured as the win ratio. Thus, we use WIN_{it} to denote the win ratio of a particular team in a particular season:

$$WIN_{it} = \beta_0 + \beta_1 Q_{it}^T + \beta_2 TIME + (V_{it} - U_{it}) \tag{6.14}$$

where $WIN_{it} = \sum \frac{W_{it}}{GP_{it}}$, W_{it} is the total number of wins and GP_{it} is the total number of games played. All other variables are defined as in equation (6.1).

Unlike North American sports, there is a high number of drawn matches in football. We therefore consider two alternative output measures. $POINTS_{it}$ is measured as total number of wins plus one-third the number of draws relative to the total number of games played, and $NEWPOINTS_{it}$ is measured as total number of wins plus one half the number of draws relative to the total number of games played. Thus:

$$POINTS_{it} = \beta_0 + \beta_1 Q_{it}^T + \beta_2 TIME + (V_{it} - U_{it}) \tag{6.15}$$

and

$$NEWPOINTS_{it} = \beta_0 + \beta_1 Q_{it}^T + \beta_2 TIME + (V_{it} - U_{it}) \tag{6.16}$$

[17] Full derivation is provided in the appendix of Battese and Coelli (1993).
[18] Heteroskedasticity can also be present in the two-sided error term (Hadri *et al.*, 1999).

where $POINTS_{it} = \sum \frac{W_{it} + 1/3(D_{it})}{GP_{it}}$, $NEWPOINTS_{it} = \sum \frac{W_{it} + 1/2(D_{it})}{GP_{it}}$ and D_{it} is the total number of games drawn[19].

Two alternative input measures are considered[20]. These are the predicted team valuation measure and the reported wage measure. While we recognise that wages is conceptually far from ideal, it is at present the only available alternative to the predicted team valuation measure. The predicted team valuation model is specified as:

$$Y_{it} = \beta_0 + \beta_1 PV_{it}^T + \beta_2 TIME + (V_{it} - U_{it}) \tag{6.17}$$

where PV_{it}^T is the predicted team valuation (see Chapter 5 for details).

The wage specification is formulated as:

$$Y_{it} = \beta_0 + \beta_1 W_{it}^C + \beta_2 TIME + (V_{it} - U_{it}) \tag{6.18}$$

where W_{it}^C is the wage information for club i in season t. Strictly speaking because our aim is to measure managerial efficiency the residual in equation (6.18) is not a manager effect. As mentioned in Chapter 4, the one-sided residual term here is difficult to interpret because the wage information represents the wages paid to all employees

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[19] In English football, teams are awarded 3 points for a win, 1 point for a draw and 0 points for a defeat. The *POINTS* measure weights a drawn match as 0.333 (compared to 0.5 for the *NEWPOINTS* measure) and can therefore be treated as a ratio of the total number of points gained to the total number of points available.

[20] We also consider the raw data which determines predicted player valuations as a third class of inputs.

(including the manager) of the football club. Even though the valuation method is our preferred measure, wages is useful for comparative purposes.

6.3 Results

The descriptive statistics for the team performance variables are presented in Table 6.1. The output measures are classified in terms of managerial mid-season changes while the input measures are classified at the level of the club. Thus, if a club does not change its manager during the season the output is based on seasonal data. If the club changes a manager once during the season we have two different outputs – one for the outgoing manager and one for the incoming manager[21]. Therefore, even though we have 126 club observations for the Premier League for the six seasons sampled we have 147 managerial observations because we include mid-season managerial changes. For example, Chelsea dispensed with the managerial services of Ruud Gullit on 12 February 1998, immediately employing Gianluca Vialli as player-manager. Based on the results up to 12 February, Chelsea had a win ratio of 0.56. From 12 February to the season end Chelsea's win ratio was 0.462. Therefore, for season 1997/98 the win ratio for Ruud Gullit would be recorded as 0.56 and the win ratio for Gianluca Vialli would be recorded as 0.462. However, the average player valuation (team quality measure) of £2.25m is assumed to be the same for both managers. While this is necessarily restrictive, it is not unreasonable. Even though incoming managers often buy and sell players in an attempt to improve team performance these changes are generally undertaken in the close season prior to the start of the following season. This gives some justification for assuming equality between the two periods.

Table 6.1 Descriptive Statistics: Team Performance Variables

	Premier League Teams (N = 126)		All Teams[a] (N = 552)	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Output				
WIN[b]	0.301	0.152	0.294	0.147
POINTS[b]	0.380	0.167	0.369	0.165
NEWPOINTS[b]	0.420	0.176	0.406	0.175
Input				
VALUE[c]	1,900,127	409,006	590,177	77,106
WAGES[d]	6,487,285	3,770,501	2,991,874	3,108,001
LEAGTOT	206.040	31.593	170.58	45.64
GLSTOT	28.437	8.497	21.145	8.71
PREVCLUB	1.912	0.386	2.15	0.59
CURRENT[e]	1.704	1.502	N/A	N/A
AGET	26.586	0.877	26.038	1.221
TOTLGT	27.213	3.092	25.59	4.09
GLST	3.451	1.029	2.94	1.02
LRDIVT	1.196	0.299	2.45	0.97

Notes: The variables relate to the team and not the individual players.
Variable Definitions: WIN = total number of wins divided by total number of games played; POINTS = total number of points divided by total number of points possible; NEWPOINTS = total number of wins plus half the number of draws divided by the total number of games played; VALUE = average player value (= team quality measure); WAGE = club wage bill; LEAGTOT= total (career) league appearances; GLSTOT = total (career) league goals; PREVCLUB = total number of previous clubs; CURRENT = dummy variable =1 if current international (i.e., has played in the last two seasons), 0 otherwise; AGET = age in year and months; TOTLGT = total (league) appearances t-1; GLST = total (league) goals t-1; LRDIVT = divisional status of club played for t-1.
[a] Premier League and Football League teams.
[b] Full set of observations (i.e., including mid-season managerial changes). Sample size = 147 for Premier League and 661 for all four divisions.
[c] VALUE 6 for Premier League and VALUE 2 for all divisions, both in pounds sterling.
[d] Sample size = 118 for Premier League and = 454 for all four divisions.
[e] Applies to VALUE 6 only (N/A = not applicable).

We see in Table 6.1 that the typical output of a Premier League team is almost identical to the typical output when all divisions, including the Premier League, are considered. In contrast, but equally as expected, the input measures show a much greater degree of variability. The average VALUE[22] is £1.9 million for the typical Premier League team, but only £0.59 million for the typical football team (if we exclude Premier League teams

[21] Providing both the incoming and outgoing manager were appointed for a minimum of 10 matches.

this value falls to below half a million). This reflects the higher quality of the average player for the typical Premier League team since VALUE is determined by a combination of the player's characteristics. We consider eight variables for a Premier League player and seven when all divisions are considered. Generally speaking, these variables correspond to the variables considered by the SOCCER TRANSFERS program in generating the VALUE variable[23]. Thus, the average player in a typical Premier League team has played professional football for about six seasons for two clubs; scores approximately one goal every seven games; is about 26 years of age and is likely to be a current international who was in the Premier League last season where he played in 27 matches scoring approximately three goals. *A priori*, we expect LEAGTOT, GLSTOT, CURRENT, AGET, TOTLGT and GLST to be positively related to the individual player's value and team output, PREVCLUB and LRDIVT to be negatively related to the individual player's value and team output.

The data is drawn from an unbalanced panel of football managers for the seasons 1992/93 to 1997/98 inclusive. Each of the models considered adopts a Cobb-Douglas (C-D) functional form. Alternative functional forms were considered (e.g., linear and quadratic), but the C-D specification consistently out-performed the alternatives[24]. The C-D stochastic frontier production function is specified as equation (6.1): win ratio (WIN) and two points ratios (POINTS and NEWWPOINTS) are alternative dependent variables to be considered; WAGE, VALUE and RAW are alternative independent variables under consideration; and TIME is entered as a control variable. With the exception of TIME, all variables are transformed into natural logarithms.

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[22] VALUE refers to PV_{it}^{T} in equation (6.17).

[23] See Chapter 5 for details. We use these 'raw' characteristics themselves as input measures when we compare alternative input and output measures.

[24] A translog interpretation is discussed in the section on alternative input and out measures.

6.3.1 Time–Invariant Managerial Efficiency

In this section we compare alternative time-invariant models. By combining equations (6.14) and (6.17) we obtain the following specification:

$$\ln WIN_{it} = \ln \beta_0 + \ln \beta_1 PV_{it}^T + \beta_2 TIME + (V_{it} - U_i) \tag{6.19}$$

Table 6.2 gives the results obtained from OLS, within estimation, GLS and ML (half-normal and truncated-normal) based on the assumption that managerial efficiency is time-invariant ($U_i = U_{it}$). The analysis here is based solely on Premier League observations in order to ease the computational burden because the efficiency scores from both the within estimation and GLS have to be calculated manually.

Table 6.2 OLS, Within, GLS and ML Estimates of a Stochastic Team Production Frontier for Premier League Teams

(Time-Invariant Managerial Efficiency)[a]

Production		OLS	Within	GLS	ML (H-N[b])	ML (T-N[b])
Variable	Parameter					
CONSTANT	β_0	-1.166 (-7.512)	-1.005 (-4.769)	-1.125 (-7.088)	-0.8012 (-6.201)	-0.824 (-8.292)
VALUE	β_1	1.364 (17.187)	1.362 (12.666)	1.352 (16.561)	1.345 (16.530)	1.341 (17.315)
TIME	β_2	-0.003 (-0.316)	-0.048 (-3.222)	-0.009 (-0.933)	-0.011 (-0.519)	-0.011 (-0.535)
Variance Parameters						
μ					0[c]	-0.457 (-1.545)
σ^2					0.223 (4.235)	0.408 (2.672)
γ					0.295 (1.310)	0.635 (3.868)
Diagnostics						
χ^2 (B-J)		140.383 (0.000)[d]				
χ^2 (B-P)		26.613 (0.000)[d]				
R^2		0.673	0.623	0.672		
F-statistic		148.44	86.41	277.54[e]		
Log-Likelihood		-82.282			-81.917	-81.324
Iterations					9	16
N		147	147	147	147	147

Notes: Asymptotic t-ratios in parentheses. Variance parameters: $\sigma^2 = \sigma_\gamma^2 + \sigma_U^2$ and $\gamma = \frac{\sigma_U^2}{\sigma^2}$

[a] The dependent variable is the natural logarithm of output (WIN).; the independent variable is the natural logarithm of VALUE[a] 6 and TIME is a control variable.
[b] H-N = half-normal distribution; T-N = truncated-normal distribution.
[c] By assumption.
[d] p-value.
[e] Chi-squared distribution.

Before comparing the parameter and efficiency estimates from the competing approaches, we note the significance of two diagnostic test statistics from the OLS estimates[25]. The Bera-Jacque (B-J) test of normality indicates sizeable non-normality and the Breusch-Pagan (B-P) test detects the presence of heteroskedasticity. At first sight these results suggest the model is inappropriate. However we expect non-normality because the error term is composed of a symmetric component (V_{it}) and an asymmetric component (U_{it}), thereby giving an asymmetric combined distribution. Non-normality is a key feature of frontier models. As a rule of thumb if the residuals do not exhibit significant non-normality then the frontier model is rejected and estimation should proceed using OLS. To deal with heteroskedasticity we re-estimated the models by re-classifying the observations in terms of club size based on number of employees (less than 125 and greater than or equal to 125). In another model, the re-classification was based on team valuation (above and below mean deviation). F-tests on the equality of the variances (pooled versus grouped) were accepted (at the 5 per cent level) in both. These tests were substantiated by the similarity of the resulting efficiency scores between the grouped and pooled observations[26]. Thus, the data can be pooled.

The coefficients for VALUE in each of the competing models are positive and statistically significant. They are also very similar in size with an output elasticity of between 1.34 and 1.36 which indicates increasing returns. The parameter estimates for VALUE tend to decrease as the required number of assumptions increases. The parameter estimate is largest for the within estimator and smallest for the ML truncated-normal (T-N) distribution. Although the differences are not large, they are consistent with the findings of Ahmad and Bravo-Ureta (1996) who compare the within estimator

[25] Recall that it is necessary to calculate OLS estimates because these are used as starting values in each of the alternative model formulations.

with the half-normal (H-N) and T-N ML distributions, and Seale (1990) who compares within, GLS and H-N.

TIME is insignificant in all models (except within) and indicates that the production frontier does not change over time (e.g., zero technical change). The overall explanatory power of the models suggest that two-thirds of the variation in the win ratio is explained by VALUE (team quality). The remaining third is attributable to random factors and the manager (i.e., managerial efficiency). The variance parameter σ^2 is significant in both the half-normal and truncated-normal ML models. The γ-parameter has a value between zero and one. The closer this value is to one, the greater the contribution of (manager) efficiency to total variability[27]. In the truncated-normal model the value of 0.635 is statistically significant at the 1 per cent level. However, the γ-parameter is insignificant (at the 10 per cent level) for the half-normal distribution. One reason for this may be because the ML estimates converged after only nine iterations in the half-normal model.

A comparison of the efficiency scores generated in the four models is given in Table 6.3[28]. While the production parameter estimates do not appear to depend on the estimation procedure the efficiency scores do. The average efficiency for the within estimator is 55 per cent; for the GLS it is 63 per cent and for the T-N and H-N it is 84 per cent and 83 per cent, respectively. Such findings are consistent with Seale (1990) and Hallam and Machado (1996). The minimum efficiency levels differ significantly more than the maximum efficiency levels. The maximum efficiency ranges from 100 per

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[26] On this basis we argue that heteroskedasticity is present in the one-sided error term but not the two-sided term. We test for this in one of the time-varying efficiency models (Section 6.3.2).
[27] Recall that this measure is only an approximation (see footnote 9, Chapter 5).
[28] We do not present corresponding efficiency scores for OLS because the production parameters from OLS are only used as starting values for the other models (see footnote 25).

cent (for within and GLS) to 91.5 per cent (H-N), while the range for the minimum efficiency level is 0.07 (within) to 0.56 (H-N). This is also reflected in the relative frequencies. Seventy per cent of managerial efficiency scores for the two ML models are located within the 80 to 90 per cent range, whereas for within estimation and GLS only 11 and 15 per cent of observations, respectively, lie within the same range.

Table 6.3 Time–Invariant Models: Summary Statistics of Managerial Efficiency Scores

Statistic	Within	GLS	H-N	T-N
Summary Measures				
Sample Mean	0.549	0.633	0.825	0.841
Standard deviation	0.163	0.103	0.059	0.073
Maximum	1	1	0.915	0.931
Minimum	0.071	0.391	0.561	0.477
Relative Frequency				
0.901 – 1	1	1	4	8
0.801 – 0.9	2	2	50	51
0.701 – 0.8	8	11	15	9
0.601 – 0.7	15	33	2	3
0.501 – 0.6	24	18	1	0
0.401 – 0.5	12	5	0	1
0.301 – 0.4	4	2	0	0
0.201 – 0.3	3	0	0	0
0.101 – 0.2	1	0	0	0
0.001 – 0.1	2	0	0	0
Pearson (Rank) Correlation Coefficients				
Within	1			
GLS	0.983 (0.992)	1		
H-N	0.926 (0.966)	0.878 (0.963)	1	
T-N	0.905 (0.966)	0.842 (0.964)	0.992 (0.999)	1
Win Ratio	0.709 (0.659)	0.733 (0.668)	0.614 (0.669)	0.583 (0.678)

Note: Definitions as Table 6.2.

While there is considerable difference in the absolute efficiency scores, the correlations are much closer (see lower part of Table 6.3). Pearson correlation coefficients and

Spearman rank correlation coefficients (in parentheses) were conducted on the four models to produce a total of six pairwise correlations. All of the Pearson correlations are above 0.84 and all of the rank correlations exceed 0.96. These values suggests that the four estimation procedures provide very similar managerial efficiency rankings.

Table 6.3 also reports correlations between the efficiency scores provided by the four estimators and win ratio. On the basis of the Pearson coefficients, GLS provides the highest correlation and the truncated-normal distribution the lowest. The rank correlations are, however, almost identical. The overall comparison of the magnitude of these correlations suggests that managerial quality should not be based on the win ratio measure alone.

Finally, Hausman specification tests (Hausman, 1978) were conducted to determine the most appropriate estimation method[29]. Hausman tests comparing the within estimator with the GLS estimator failed to reject the null hypothesis of no correlation between effects and regressors[30] $\left(E(U_{it} | Q_{it}^{T}) = 0\right)$. Similarly, tests of the distributional assumptions (GLS versus H-N and GLS versus T-N) also fail to reject the null hypothesis. Finally, comparing H-N to within and T-N to within (testing both the correlation and distributional assumptions) strongly rejected the within estimator against both ML formulations. Our results suggest that ML is the preferred estimation method. In contrast, previous studies have tended to favour the within estimator (e.g., Ahmad

[29] Based on the Wald criteria for a single coefficient (Greene, 1997a):

$$W = \left(\hat{\beta}_1^{FE} - \hat{\beta}_1^{RE}\right)\left[Var(\hat{\beta}_1^{FE}) - Var(\hat{\beta}_1^{RE})\right]^{-1}\left(\hat{\beta}_1^{FE} - \hat{\beta}_1^{RE}\right)$$

where, for example, FE and RE refer to the parameter estimates from the within and GLS estimators, respectively. The test statistic has a Chi-square distribution.

[30] Test statistic of 0.03. In contrast, the multiple coefficient result (i.e., including the time variable) rejects the null of no correlation (test statistic of 11.59). TIME, however, is only a control variable and has no direct interpretation.

and Bravo-Ureta, 1996; Seale, 1990). Based on a generalised likelihood ratio test[31], the half-normal specification was preferred to the truncated-normal specification. However, likelihood ratio tests reject (at the 10 per cent level) estimation of both the half-normal and truncated-normal specifications in favour of the traditional production function (e.g., OLS).

Paradoxically, therefore, Hausman Tests reject the use of panel data models in favour of ML alternatives. But on the basis of likelihood ratio tests neither ML model is statistically superior to OLS. One possible reason for this is that time-invariance, however measured, is not an accurate representation of managerial efficiency.

6.3.2 Time-Varying Managerial Efficiency

The models considered so far assume managerial efficiency is time-invariant. Time-varying efficiency becomes more appropriate as the number of time-periods increases. Although we have a relatively small number of time-periods (seasons), time-varying efficiency may still be more suitable because of the conflicting results obtained from the time-invariant models.

Although several studies have compared the different estimation procedures for time-invariant efficiency (e.g., Schmidt and Sickles, 1984; Seale, 1990; Hallam and Machado, 1996) only Ahmad and Bravo-Ureta (1996) have carried out a similar exercise (comparing ML with FE) for models with time-varying efficiency.

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[31] Likelihood ratio tests are preferred to F tests because the former do not require the assumption of normality.

In the case of time-varying efficiency there are two concurrent problems which need to be addressed: the choice of model and the choice of estimation procedure. According to Kumbhakar *et al.* (1997) the literature suggests a number of different model specifications, requiring different methods of estimation. For example, the nature of the models specified by Cornwell *et al.* (1990) and Lee and Schmidt (1993) lend themselves to estimation using within, GLS and H-T. In contrast the models of BC (1992) and BC (1995) can only be estimated using ML methods. A further problem for the researcher is that each time-varying model has a different temporal structure. The model of BC (1992) being the most restrictive, while the model of BC (1995) is the least restrictive (although it does require knowledge of the inefficiency effects).

Because of these problems, and the fact that we are conscious of the number of results to be discussed, we restrict our discussion to a comparison of the model of BC (1992) with the model of BC (1995). These models are at opposite ends of the spectrum of temporal structures. Moreover, they can only be estimated using ML methods. One potential drawback of using the ML approach is the difficulty in finding an appropriate distribution for the efficiency term. However, our results for time-invariant efficiency suggest this is not a major problem here.

We compare three time-varying ML models[32]. The results are presented in Table 6.4. BC (1992) is the time-varying efficiency model as a deterministic function of time, BC1 (1995) is the inefficiency effects model with simply an intercept term and BC2 (1995) is the inefficiency effects model which includes 12 managerial human capital

[32] These models have been automated in the statistical program FRONTIER 4.1. See Chapter 5 for details of the program.

characteristics[33] which are thought to influence inefficiency. The main reason for including BC1(1995) is to see whether the 12 inefficiency effects are jointly significant or not. In order to make meaningful comparisons with the time-invariant results we continue to use Premier League observations.

Compared to the parameter estimates generated under the various time-invariant models, the VALUE coefficient is smaller (approximates constant returns) but is significant at the 1 per cent level. TIME is now positive, although only statistically significant under BC (1992). The fact that η is negatively signed and significant in BC (1992) suggests that managerial efficiency declines (inefficiency increases) over time[34]. The positive sign of the time trend (δ_{12}) in BC2 (1995) also suggests managerial inefficiency increases (efficiency decreases) over time[35].

There is also considerable difference between the variance parameters generated in the time-invariant ML models and the time-varying ML models. The γ-parameter is much higher in each of the time-varying models. This indicates that efficiency (or, more precisely, lack of) is the major cause of residual variation (recall that γ approximates the ratio of variance of efficiency to the composed residual). The size of the parameters for σ^2 are also substantially increased[36].

[33] An examination of these human capital variables is provided in Chapter 7, hence, with the exception of the intercept and time variables, they are not reported here. Other inefficiency effects (i.e., quadratics, playing positions and club-specific factors) are also reserved until Chapter 7 to enable us to develop the set of inefficiency effects heuristically. Thus for the time being we concentrate on a parsimonious set of human capital factors. Nevertheless, the results here are little changed when all potential inefficiency effects are included.

[34] This is consistent with the finding of Hofler and Payne (1996) for American football.

[35] For the inefficiency effects, a positive sign refers to an increase in inefficiency and a negative sign means a decrease in inefficiency.

[36] We did test the three time-varying specifications using a different transformation. The σ^2-parameter estimates were equal to 1.039, 0.080 and 0.223, respectively. These are considerably lower than those reported in Table 6.4 and are more comparable with the corresponding parameters for the time-invariant models. Nevertheless, the other parameter estimates were broadly the same under both transformations and, more importantly, the efficiency scores were almost identical.

Table 6.4 ML Estimates for Time-Varying Efficiency and Inefficiency Effects Models (Premier League Teams)

Production		BC (1992)		BC1 (1995)		BC2 (1995)	
Variable	Parameter	ML Estimate	t-value	ML Estimate	t-value	ML Estimate	t-value
CONSTANT	β_0	-1.092	(-11.991)	-0.799	(-13.195)	-0.868	(-13.505)
VALUE	β_1	1.261	(17.085)	1.062	(20.051)	1.060	(14.292)
TIME	β_2	0.080	(3.308)	0.012	(0.787)	0.023	(1.401)
Inefficiency Effects[a]							
CONSTANT	δ_0			-24.211	(-1.109)	-3.893	(-1.944)
TIME	δ_{12}					0.407	(2.898)
Variance Parameters							
	μ	-4.680	(-3.349)				
	η	-0.567	(-5.065)				
	σ^2	5.586	(1.901)	8.766	(1.160)	1.138	(3.422)
	γ	0.983	(77.798)	0.995	(232.046)	0.962	(60.837)
Log-likelihood		-74.799		-61.637		-53.174	
Iterations		39		28		25	
N		147		147		147	

Notes: BC (1992) = Traditional stochastic frontier model, where $\mu \neq 0$ $\eta \neq 0$; BC1 (1995) = Inefficiency effects model, intercept only; BC2 (1995) = BC1 (1995) incorporating 12 inefficiency effects.
[a] Only one inefficiency effect (a time trend) is reported. The remaining inefficiency effects parameters (δ_1 to δ_{11}), and other inefficiency effects (including incentive factors) are discussed in Chapter 7.

Likelihood ratio tests were conducted on the three models (Table 6.5). In each case λ follows the Chi-square distribution. The null hypothesis – that estimation should proceed using an appropriate OLS estimation – is rejected in all three models, so a stochastic production frontier is justified[37]. Also, we are able to reject the null hypothesis that inefficiency is half-normal (i.e., $\mu = 0$) and, more importantly, time-invariant ($\eta = 0$). Thus, time-invariance is not an adequate representation of managerial efficiency in English football.

Table 6.5 Generalised-Likelihood Ratio Tests for the Distribution of Managerial Efficiency: BC (1992), BC1 (1995), BC2 (1995)

Null Hypothesis	Log-Likelihood (L_R)	λ	$\chi^2_{0.95}$	Decision
BC (1992)				
$\gamma = 0$	-82.282	14.966	2.706*	Reject H_0
$\mu = \eta = 0$	-81.917	14.236	5.991	Reject H_0
BC1 (1995)				
$\gamma = \delta_0 = 0$	-82.282	41.290	23.069*	Reject H_0
BC2 (1995)				
$\gamma = \delta_0 .. \delta_{12} = 0$	-82.282	58.216	23.069*	Reject H_0

Notes: Lambda (λ) is found using the following likelihood ratio test formula $\lambda = -2\{L(_R)-L(_{UR})\}$ where $L(_R)$ and $L(_{UR})$ refer to the log-likelihood function of the null and alternate hypothesis, respectively.
* Mixed Chi-square critical values (Table 1, Kodde and Palm, 1986).

Notice, however, that for hypothesis tests which involve γ the usual Chi-square distribution does not apply because γ is a bounded variable which can only take values between 0 and 1 (this also applies to the time-invariant models considered earlier). To test the hypothesis that $\gamma = 0$ versus the alternative $\gamma > 0$ the likelihood ratio statistic has a mixed Chi-square distribution, $(1/2)\chi_0^2 + (1/2)\chi_1^2$ (Coelli, 1993). Critical values for the single restriction, and restrictions which include the δ-parameters, are obtained from Table 1 of Kodde and Palm (1986). Incorporating the mixed Chi-square distribution does not seriously alter the results for the time-varying models because the test statistics are far greater than the critical values. However, they do alter the findings for the time-invariant models. The likelihood ratio test of the null hypothesis of OLS versus the alternative hypothesis of truncated-normal is now rejected at the 10 per cent level.

[37] Compare this to the equivalent test we reported for time-invariance.

The above hypothesis test indicates that BC2 (1995) is the preferred production frontier model because it has the highest likelihood ratio, thus rejecting the null hypothesis with a greater degree of accuracy. However, direct comparisons between BC (1992) and the inefficiency effects models are not entirely appropriate because the formulations are non-nested. Because of this we compare all three models in terms of inefficiency scores. These are reported in Table 6.6. The sample mean for BC (1992) is noticeably higher than those obtained from the inefficiency effects models. In part, this may reflect the tendency for over-estimation of managerial efficiency in models which suffer from heteroskedasticity (e.g., Caudill *et al.*, 1995). The relative frequencies also suggest that there is a greater degree of dispersion under the inefficiency effects model.

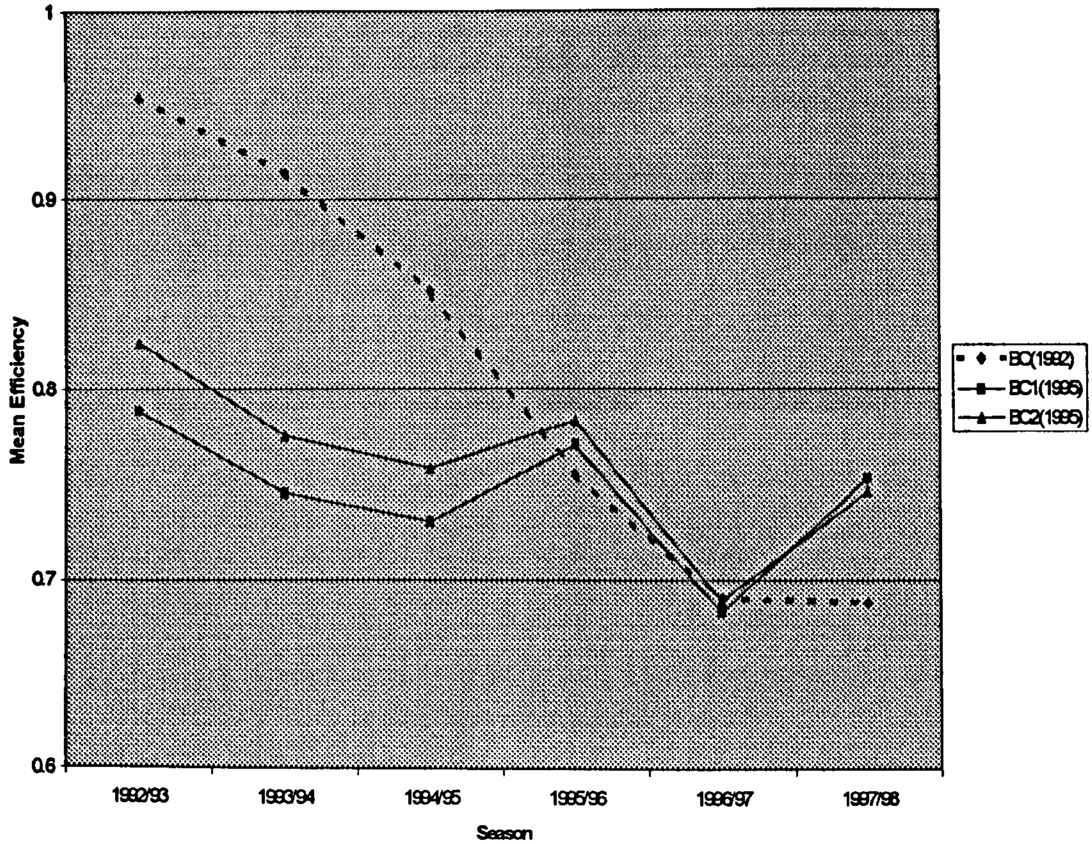
Analysing mean efficiency by season (middle section of Table 6.6 and also Figure 6.1) demonstrates how BC (1992) and the inefficiency effects model differs. Efficiency in BC (1992) decreases towards the last observed point. Alternatively, inefficiency increases to last observed point (average mean inefficiency increases from 5 per cent in 1992/93 to 31 per cent in 1997/98). This is a consequence of imposing a specific temporal pattern on efficiency. With the inefficiency effects model efficiency (inefficiency) fluctuates over the sample period, although the overall trend is again downward (upward). Not surprisingly, the correlation coefficients and rank correlations between BC (1992) and BC1 (1995) and BC (1992) and BC2 (1995) are low, whilst the correlation coefficients between BC1 (1995) and BC2 (1995) are close to one. The fact that it is not one indicates the presence of heteroskedasticity in the one-sided error term. Also, BC1 (1995) and BC2 (1995) produce substantially higher correlations with win ratio than BC (1992). However, none of the correlations are particularly high.

Table 6.6 Time–Varying Models: Summary Statistics of Managerial Efficiency Scores

Statistic	BC (1992)	BC1 (1995)	BC2 (1995)
Summary Measures			
Sample Mean	0.813	0.744	0.762
Standard deviation	0.155	0.174	0.173
Maximum	0.979	0.940	0.948
Minimum	0.164	0.080	0.081
Mean by Season			
1992/93	0.954	0.788	0.824
1993/94	0.914	0.745	0.775
1994/95	0.851	0.730	0.758
1995/96	0.755	0.770	0.783
1996/97	0.690	0.683	0.689
1997/98	0.688	0.753	0.746
Relative Frequencies			
0.901 – 1	54	15	20
0.801 – 0.9	43	59	61
0.701 – 0.8	25	33	33
0.601 – 0.7	10	17	12
0.501 – 0.6	7	11	10
0.401 – 0.5	4	3	3
0.301 – 0.4	1	2	2
0.201 – 0.3	2	4	4
0.101 – 0.2	1	2	1
0.001 – 0.1	0	1	1
Pearson (Rank) Correlation Coefficients			
BC (1992)	1		
BC1 (1995)	0.592 (0.418)	1	
BC2 (1995)	0.655 (0.529)	0.984 (0.963)	1
Win Ratio	0.376 (0.281)	0.758 (0.774)	0.737 (0.746)

Figure 6.1 Mean Managerial Efficiency Over Time:

BC (1992), BC1 (1995) and BC2 (1995)



6.3.3 Comparing Alternative Input and Output Specifications

The results for time-varying managerial efficiency indicate that the inefficiency effects model is preferred. Table 6.7 presents production frontier estimates using BC2 (1995) for all teams under alternative input and output specifications. To begin with we alter the input measures (using WIN to measure output) and then we adjust the output measure (using VALUE to measure input). WINVALUE shows that increasing the sample to include managerial observations from both the Premier League and Football League has little impact on the ML estimates. However, the standard errors are now much lower resulting in higher significance levels[38].

[38] Heteroskedasticity was again tested for and a stronger presence was detected. This is not surprising given the considerable differences in the size of the clubs. However, we continue to assume heteroskedasticity is only present in the in the one-sided error term because the efficiency results obtained for the separate divisions are almost identical to the ones produced for the pooled sample.

Table 6.7 ML Estimates of a Stochastic Team Production Frontier: A Comparison of Various Input / Output Specifications (All Teams)

Variable	MODEL				
Dependent Variable	WIN	WIN	WIN	POINTS	NEWPOINTS
Explanatory Variable	VALUE	RAW	WAGE	VALUE	VALUE
Production Variables	ML Estimate (t-value)	ML Estimate (t-value)	ML Estimate (t-value)	ML Estimate (t-value)	ML Estimate (t-value)
CONSTANT	-0.847	-0.816	-0.837	-0.662	-0.582
	(-25.570)	(-25.508)	(-19.915)	(-19.466)	(-18.993)
VALUE	1.112			1.074	1.051
	(35.044)			(43.795)	(44.422)
WAGES			0.683		
			(19.091)		
LEAGTOT		-0.135			
		(-1.585)			
GLSTOT		0.074			
		(1.341)			
PREVCLUB		-0.257			
		(-4.458)			
AGET		1.629			
		(14.634)			
TOTLGT		0.018			
		(0.175)			
GLST		0.225			
		(4.280)			
LRDIVT		-0.366			
		(-5.428)			
TIME	0.017	0.006	0.025	0.009	0.011
	(1.957)	(0.712)	(2.374)	(1.416)	(1.559)

Table 6.7 – *Continued*

Variable	MODEL				
Dependent Variable	WIN	WIN	WIN	POINTS	NEWPOINTS
Explanatory Variable	VALUE	RAW	WAGE	VALUE	VALUE
Inefficiency Effects					
CONSTANT (δ_0)	-9.697	-13.185	-10.027	-5.820	-4.538
	(-2.739)	(-2.775)	(-2.435)	(-1.844)	(-2.306)
TIME (δ_{12})	0.306	0.218	0.548	0.146	0.096
	(2.735)	(2.895)	(2.964)	(1.434)	(1.830)
Variance Parameters					
σ^2	1.315	1.517	2.274	0.639	0.549
	(3.470)	(2.734)	(2.860)	(2.380)	(3.031)
γ	0.951	0.969	0.970	0.921	0.918
	(82.984)	(85.035)	(87.725)	(27.845)	(30.957)
Log –likelihood	-244.296	-186.490	-311.719	-87.435	-44.912
Iterations	33	42	31	39	36
N	661	661	541[a]	661	661

Note: As Table 6.4.
[a]The number of observations sampled for the wage specification is less than the others because of the incomplete nature of the data.

The WINRAW and WINWAGE columns illustrate the effect of changing the input measure. WINRAW is essentially a robustness check on the adequacy of the VALUE input. It enters the variables which determine VALUE directly into the production frontier (i.e., right-hand side variables in equation (4.4)). Thus, for WINRAW we have eight production parameters (LEAGTOT, GLSTOT, PREVCLUB, AGET, TOTLGT, GLST, LRDIVT and TIME). With the exception of LEAGTOT, all of the VALUE characteristics variables have the expected sign. One reason why both LEAGTOT and TOTLGT, which is only weakly significant, perform poorly may be due to the inclusion of the AGET variable. As expected, AGET has the strongest positive effect on a team's win ratio; teams are less successful if they have too many young and inexperienced players[39]. The smaller sample size for the WINWAGE specification reflects the difficulties in obtaining wage data. The results show smaller parameter estimates and smaller t-ratios when compared to WINVALUE. POINTSVALUE and NEWPOINTSVALUE provide parameter estimates when we alter the output measure but retain VALUE as the input measure. These two models provide similar parameter estimates but the significance levels are generally lower when compared with WINVALUE. This is particularly true of the variance parameters.

The production variable TIME has a positive yet weak effect in all of the models. It appears to be strongest under the WINWAGE specification. The coefficient of the time variable (δ_{12}) in the inefficiency effects model is positive in each of the five specifications, although it is more significant when WIN is the output measure. This implies that managerial efficiency decreases (or inefficiency increases) over time, regardless of how the stochastic production frontier is estimated. For the variance

[39] We did experiment with a translog specification to see whether age squared was negative. However, only three variables, in addition to Cobb-Douglas specified parameters, were statistically significant

parameter γ is close to one, ranging from 0.92 (NEWPOINTSVALUE) to 0.97 (WINWAGE). The rankings for γ are identical to the rankings for σ^2.

In Table 6.8 two hypothesis tests are conducted on each model. The first (H_0: $\gamma = \delta_0 .. \delta_{12} = 0$) considers whether inefficiency is present. The second (H_0: $\delta_1 ... \delta_{12} = 0$) considers whether the coefficients in the inefficiency effects model are zero. If the null hypothesis is accepted in the latter, the inefficiency effects model should only include δ_0 (BC1(1995)). The null hypothesis of zero inefficiency is strongly rejected in all five models. As before, this means that the OLS specification is inappropriate. The null hypothesis which specifies that all inefficiency effects are zero is rejected in the models which use the win ratio as the output measure. But the null is accepted using the other output measures. It appears therefore that the inefficiency effects for football managers using POINTS and NEWPOINTS are independently and identically distributed.
This occurs even though there is a very strong correlation between the three output measures (the correlation between win ratio and points ratio is 0.973; the correlation between win ratio and new points ratio is 0.939 and the correlation between points and new points is 0.993). Also, the correlations between the various output measures exceed the correlation between VALUE and WAGE (0.808).

(TOTLGT squared, the cross-product of AGET and PREVCLUB and the cross-product of TOTLGT and LRDIVT).

Table 6.8 Generalised-Likelihood Ratio Tests for the Distribution of Managerial Efficiency Effects: Various Input / Output Specifications

Null Hypothesis	Log-Likelihood (L_R)	λ	$\chi^2_{0.95}$	Decision
WINVALUE				
H_0: $\gamma = \delta_0 ... \delta_{12} = 0$	-304.881	121.17	23.069*	Reject
H_0: $\delta_1 ... \delta_{12} = 0$	-256.553	24.514	21.03	Reject
WINRAW				
H_0: $\gamma = \delta_0 ... \delta_{12} = 0$	-242.671	112.362	23.069*	Reject
H_0: $\delta_1 ... \delta_{12} = 0$	-197.738	22.496	21.03	Reject
WINWAGE				
H_0: $\gamma = \delta_0 ... \delta_{12} = 0$	-367.763	112.088	23.069*	Reject
H_0: $\delta_1 ... \delta_{12} = 0$	-325.576	27.714	21.03	Reject
POINTSVALUE				
H_0: $\gamma = \delta_0 ... \delta_{12} = 0$	-119.638	64.406	23.069*	Reject
H_0: $\delta_1 ... \delta_{12} = 0$	-95.062	15.254	21.03	Accept
NEWPOINTSVALUE				
H_0: $\gamma = \delta_0 ... \delta_{12} = 0$	-74.651	59.478	23.069*	Reject
H_0: $\delta_1 ... \delta_{12} = 0$	-51.335	12.846	21.03	Accept

Notes: As Table 6.5.

Given that the model specifications are again non-nested, various summary measures of the efficiency scores provided by these five models are presented in Table 6.9. For clarity, mean efficiency for each model by season is illustrated in Figure 6.2 and mean efficiency for each model by division is illustrated in Figure 6.3. Average efficiency tends to decline over time, but varies in magnitude between the models. For example, average efficiency in the WINWAGE model falls by about 9 per cent between the first season and the last season, whereas for NEWPOINTSVALUE the difference is only 2 per cent. Average efficiency is highest at 86 per cent in the POINTSVALUE and NEWPOINTSVALUE models and lowest in the WINWAGE specification (72 per cent).

Table 6.9 Various Input / Output Specifications: Summary Statistics of Managerial Efficiency Scores

Model	WIN VALUE	WIN RAW	WIN WAGE	POINTS VALUE	NEWPOINTS VALUE
Summary Statistics					
Sample Mean	0.794	0.794	0.717	0.855	0.864
Standard deviation	0.130	0.137	0.178	0.085	0.079
Maximum	0.951	0.955	0.951	0.958	0.960
Minimum	0.094	0.127	0.053	0.142	0.157
Mean by Season					
1992/93	0.826	0.815	0.780	0.867	0.872
1993/94	0.819	0.812	0.762	0.869	0.878
1994/95	0.786	0.780	0.700	0.850	0.860
1995/96	0.786	0.788	0.693	0.853	0.862
1996/97	0.784	0.787	0.686	0.848	0.859
1997/98	0.767	0.784	0.694	0.842	0.853
Mean by Division					
Premier	0.782	0.772	0.715	0.849	0.860
Division 1	0.797	0.801	0.713	0.855	0.864
Division 2	0.800	0.794	0.718	0.857	0.865
Division 3	0.798	0.807	0.725	0.858	0.865
Relative Frequency					
0.901 – 1	82	99	26	211	240
0.801 – 0.9	315	329	201	343	321
0.701 – 0.8	163	121	136	74	75
0.601 – 0.7	57	50	69	17	13
0.501 – 0.6	15	29	38	12	10
0.401 – 0.5	12	13	30	2	0
0.301 – 0.4	7	13	20	0	1
0.201 – 0.3	7	5	12	1	0
0.101 – 0.2	1	2	7	1	1
0.001 – 0.1	2	0	2	0	0
Pearson (Rank) Correlation Coefficients					
WINVALUE	1				
WINRAW	0.871 (0.777)	1			
WINWAGE	0.751 (0.671)	0.713 (0.580)	1		
POINTSVALUE	0.922 (0.949)	0.744 (0.666)	0.667 (0.615)	1	
NEWPOINTSVAL	0.847 (0.898)	0.662 (0.600)	0.614 (0.581)	0.984 (0.989)	1
OUTPUT[a]	0.626 (0.658)	0.716 (0.795)	0.659 (0.646)	0.557 (0.556)	0.545 (0.529)

[a] Refers to win ratio for WINVALUE, WINRAW and WINWAGE, points ratio for POINTSVALUE; and new points ratio for NEWPOINTSVALUE.

Figure 6.3 (and the middle part of Table 6.9) illustrates that there is very little difference in the mean efficiency scores across the divisions. Surprisingly, it is lowest overall in the Premier League. The pressure on managers to be successful in this league in particular may well be a contributing factor here[40]. Consistent with Figure 6.2, mean efficiency is highest when POINTS is the output measure and lowest when WAGE is the input measure.

Perhaps the most striking piece of information however is the considerable variation between the models in terms of the correlation coefficients (lower part of Table 6.9). Whilst the correlations between POINTSVALUE and NEWPOINTSVALUE and WINVALUE and POINTSVALUE are similar, the correlations for the various input specifications show a much weaker level of association. For both Pearson correlations and rank correlations the WINWAGE specification shows the least level of association with the other specifications. Overall, these results suggest the choice of input and output measure is as equally important as the choice of estimation procedure.

[40] Other possibilities are considered in Chapter 7.

Figure 6.2 Mean Managerial Efficiency over Time:

Various Input/Output Specifications

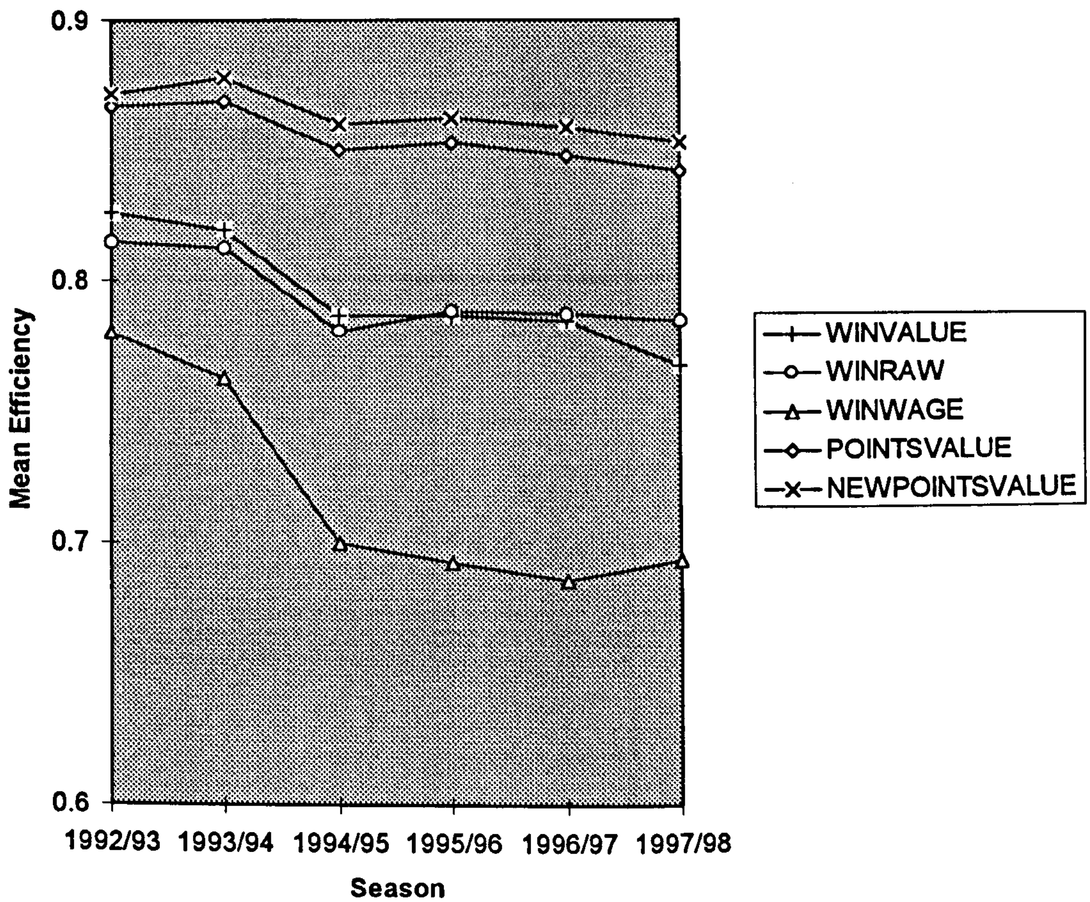
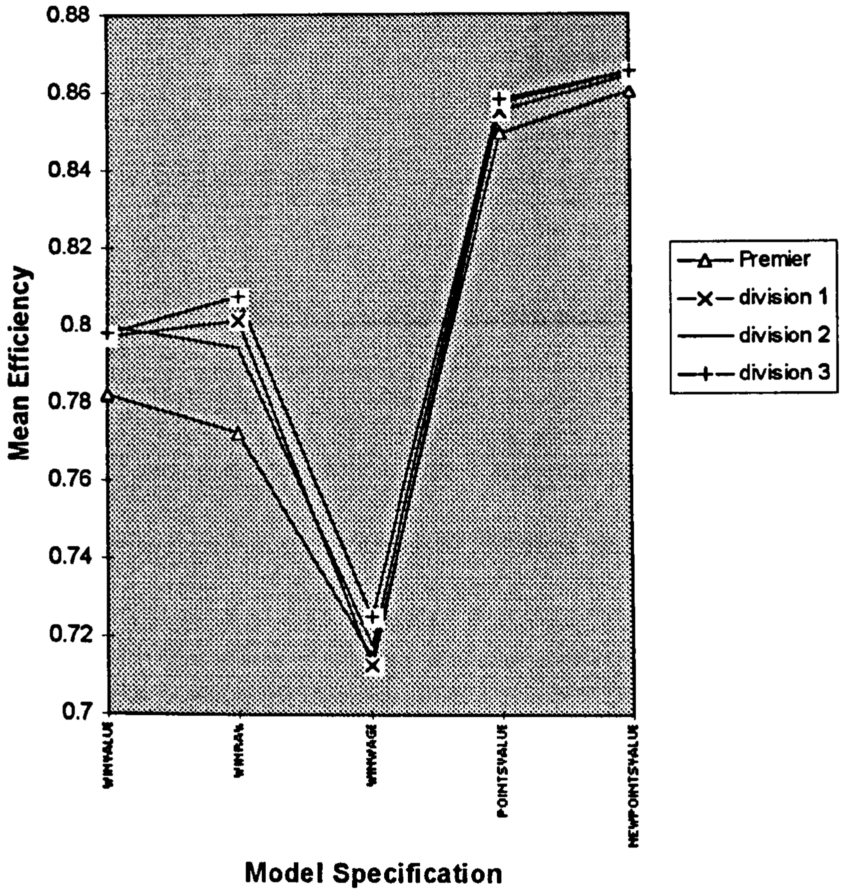


Figure 6.3 Mean Managerial Efficiency by Division:

Various Input/Output Specifications



6.4 Summary

This chapter has used stochastic frontier analysis to estimate the efficiency of an unbalanced panel of football managers over the period 1992-98. In particular we have examined how alternative estimation procedures and different measures of input and output affect efficiency estimates.

Efficiency can be modelled as time varying or time invariant. In the time invariant case we compared fixed effects, random effects and maximum likelihood (ML) estimation. The results indicate that the various estimation procedures, although producing quite different mean efficiency scores, yield very similar efficiency rankings and the results favour the ML method. For time-varying efficiency we compared the results of the time-varying effects model (BC, 1992) with the inefficiency effects model (BC, 1995). On the basis of statistical tests, the time-varying specification is preferred to a time-invariant one. In contrast, the choice between BC (1992) and BC (1995) cannot be made on statistical grounds. We favour the inefficiency effects model (BC2(1995)) because it is more flexible such that it does not impose a specific temporal pattern on the efficiency, and, it provided a higher likelihood ratio score.

Finally, we used the inefficiency effects model to examine how the reported managerial efficiency scores are affected by the choice of input and output measures. Issues regarding the choice of production variables are rarely emphasised. The reason for this seems to be because limitations in the data preclude possible alternatives. We find the efficiency scores are just as sensitive to the choice of input and output measure as to the choice of estimation procedure. In the cases considered, replacing the win ratio output measure with either of the two alternative points measures - using the same input measure - leads us to accept the null hypothesis that the inefficiency effects are not significantly different from zero. On the input side, the wage measure produced considerably lower efficiency scores (between 5 and 10 per cent, on average) compared with the predicted value measure. It also produced a lower level of statistical association.

The implication of this is that studies which attempt to measure efficiency using a stochastic production frontier must not only correctly specify the equation in terms of functional form and estimation procedure, but also consider alternative input and output measures (where possible). Thus, in circumstances where competing input and output measures exist, researchers should compare and contrast the resultant efficiency scores using all the information available. If the choice of input and output measures is not accounted for in the stochastic production frontier specification then conclusions regarding managerial efficiency estimates are likely to be inappropriate.

In the next chapter we present a detailed analysis of the determinants of managerial efficiency using human capital and incentive (effort) factors.

CHAPTER 7

EMPIRICAL RESULTS II:

INVESTIGATING THE SOURCES OF MANAGERIAL EFFICIENCY

7.1 Introduction

The manager has a pivotal role to play in the performance of a football club. The decisions he takes affect not only the outcome of the game, but also the financial performance of the club (there is a high correlation between a team's win ratio and club revenue[1]). Even though football clubs vary in size, all managers face a common objective (i.e., to win football matches). Also, they are in charge of a similar number of workers (players)[2] and work in similar environments (i.e., a football stadium). The manager's main function concerns resource allocation decisions: team selection and player recruitment.

Usually the manager is evaluated in terms of the number of matches won (i.e., achieving a promotion or winning trophies). When a manager is judged to be performing sub-optimally he is usually dismissed and a replacement is found. This occurs with alarming regularity. Of the 319 managerial spells observed in this study, 72 per cent

[1] Dobson and Goddard (1998).

[2] This refers to first-team players rather than squad players because squad sizes vary enormously.

lasted less than three seasons and only 2.5 per cent of managers were with the same club throughout our sample period (August 1992 to May 1998). In Chapter 6 we presented an objective way of measuring managerial performance. The efficiency of each manager is generated by taking into account the quality of the playing resources at his disposal. We found that the efficiency scores are just as sensitive to the choice of the production parameters (i.e., input and output measures) as to the choice of estimation procedure.

An important question to address as far as policy is concerned is whether there is any systematic pattern to the sources of efficiency. Knowledge of the determinants of efficiency is crucial to understanding managerial performance. We conjecture that variations in managerial efficiency arise principally from two main sources. Firstly, managers have varying levels of experience, motivation and leadership qualities. Secondly, football clubs differ in employment size, they have different policies regarding the level of pay and the form pay takes and they differ according to the frequency with which they change the manager. As noted in Chapter 4, we classify the first category as human capital factors and the second as incentive factors.

Within these two categories we attempt to specifically address two areas of economic debate. First, we attempt to reconcile the human capital interpretation of managerial efficiency from the signalling stance. Specifically, does human capital actually improve performance (make the manager more efficient) or is it simply used as a signal? When a club fires a manager it does not have full information about the "true" managerial abilities (i.e., efficiency) of a potential replacement. Therefore, the hiring process is conducted on the basis of the manager's attributes (level of playing experience and level of managerial experience). These attributes provide a signal of the manager's true level of ability. In accordance with the signalling literature, these attributes may or may not result in the "true" level of efficiency being realised. Our aim here is to test whether human capital accumulation improves efficiency, and to determine which factors are most important.

Secondly, and slightly more ambitiously, we attempt to reconcile human capital effects from agency determinants of managerial efficiency. No matter how skilled the manager is (in terms of his human capital), firm-specific factors, particularly the role of incentives, may influence the level of effort the manager delivers. In Chapter 4 we suggested that information asymmetry – the cause of agency problems – is less likely in sporting clubs than in other industries. This is because the production process in sporting contests is observed – by the paying spectator, the armchair fan and the club's owners (chairpersons, directors and, increasingly, shareholders). Hence, the performance of football managers, through the effort and performance of the players, can be more readily identified. However, effort levels of managers (managerial incentives) within the football industry may vary because clubs are of different size, and they have different policies on how they pay the manager and the frequency with which management is changed.

As discussed in Chapter 1 much of the agency literature is theoretical. Even so, a growing number of studies have conducted empirical tests of the use of incentives using remuneration data. Similar data has also been used to determine the relationship between human capital accumulation and earnings. However, earnings data is only an indirect measure of individual performance and by itself cannot establish whether human capital or incentive mechanisms actually improves performance. As we have said all along, the advantage of sports data is that the identification of production inputs (both players and management) is unambiguous. To date no previous study has attempted to measure human capital and incentive (effort) factors at the level of the football manager.

In sum, the main aim of this chapter is to provide a link between experience and efficiency and incentives and efficiency. This information will assist owners in recruiting the "right" manager and in creating the "right" kind of incentives once the manager is hired.

A further question to be addressed is even if human capital and incentives influence managerial efficiency does the manager actually make that much of a difference to team performance? One benefit of generating efficiency scores for each manager is that we can identify the potential improvements in team performance were the manager to operate at the optimal efficiency level. In addition, the efficiency scores can also be used to analyse the effects of succession and the timing of a managerial termination.

7.2 Model Specification

The framework used to investigate the managerial inefficiency effects follows that of Battese and Coelli (1995) outlined in Chapter 6[3]. That is:

$$Y_{it} = \beta_0 + \beta_1 Q_{it}^T + \beta_2 TIME + (V_{it} - U_{it}) \qquad (7.1)$$

The variables in equation (7.1) are as defined in equation (6.1): Y_{it} is the measure of output (WIN, POINTS or NEWPOINTS) and Q_{it}^T is a singular measure of team quality

(VALUE or WAGES)[4]. *TIME* is a control variable and β_0, β_1, and β_2 are unknown parameters. Finally, V_{it} is a normally distributed two-sided random error term and U_{it} is a non-negative truncation (at zero) distributed as $N(Z_{it}\delta, \sigma_U^2)$ such that:

$$Z_{it} = \delta_0 + q_{it}^M \delta + e_{it}^M \delta + \delta_t TIME \tag{7.2}$$

Equation (7.2) is known as the inefficiency effects model[5]. The vector Z_{it} is a set of time-varying human capital aspects of the manager (q_{it}^M) and a set of firm-specific characteristics of the club (e_{it}^M). In addition we have an intercept term (δ_0) and a time trend (*TIME*)[6]. We assume the specification is linear.

7.3 Managerial and Club Characteristics

Most of the previous studies that use the stochastic production frontier technique to measure efficiency have only given cursory consideration to the sources of efficiency. Part of the reason lies in the availability and quality of the data. Previous efficiency work, particularly in agriculture, has generally only been able to include the age and education or experience (measured in absolute number of years) of the manager and a few firm-specific effects (e.g., irrigation methods, use of fertilisers and availability of credit).

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[3] Recall that this is the preferred model specification in Chapter 6.
[4] Alternatively we could use the variables which determine the predicted transfer valuation (i.e., the RAW characteristics).
[5] See Chapters 2 and 6 for more details on this model.
[6] These two variables were previously reported in Chapter 6.

In contrast, data on English football managers and the characteristics of English football clubs is more widely available and not subject to the same kind of measurement difficulties. As detailed in Chapter 3, and again in Chapter 5, the sports (football) industry is a great provider of information on clubs, managers and players. Having said this surprisingly few of the efficiency studies in team sport have investigated the causes of efficiency. Only Porter and Scully (1982) in a somewhat dated paper provide anything like an adequate consideration of the sources of efficiency for baseball managers.

Table 7.1 provides definitions of the manager-specific and club-specific variables, together with predicted signs, that are thought to influence managerial efficiency[7].

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[7] See Chapter 5 for a discussion of the data sources for these variables.

Table 7.1 Managerial and Club Characteristics

Variable	Expected Sign[a]	Definition
MANAGE	(?)	Manager's age in years and months at the start of August of the season in question. For example, a manager born in February 1960 would be aged 37.5 in August 1997[b].
LEAGAPP	(-)	Total career league appearances made, including overseas appearances where known.
CLUBSP	(-?)	Total number of clubs the manager played for during his playing career. If a manager plays for the same club more than once during his playing career it is recorded as a different club. Hence we measure total number of playing spells (both permanent and temporary (e.g. on loan), unless the temporary spell was later transferred to a permanent position) rather than the total number of different clubs played for.
CAPS	(-)	Total number of full international (including substitute) appearances gained as a player.
U2123	(-)	Total number of under 21 and under 23 international appearances.
PLAYMAN	(+)	Dummy Variable = 1 if manager also played for club during the season under review; 0 otherwise.
MMBTJ	(-)	Total months managing prior to current appointment.
CLUBSM	(-?)	Total number of managerial appointments.
MMDIVIN	(-)	Total months managing in current division.
MMCC	(-)	Total months managing current club.
CHASCLUB	(-)	Dummy variable = 1 if manager has ever been an assistant or coach at current club; 0 otherwise.
PLAYCLUB	(-)	Dummy variable = 1 if manager played for current club (pre-appointment); 0 otherwise
PREVSPEL	(-)	Dummy variable = 1 if manager had a previous managerial appointment at current club; 0 otherwise.
GOALKEEP	(-)	Dummy variable = 1 if manager was classified as being a goalkeeper during his playing career; 0 otherwise.
DEFENDER	(-)	Dummy variable = 1 if manager was classified as being a defender during his playing career; 0 otherwise.
MIDFIELD	(-)	Dummy variable = 1 if manager was classified as being a midfielder during his playing career; 0 otherwise.
FORWARD	(-)	Dummy variable = 1 if manager was classified as being a forward during his playing career; 0 otherwise.
WAGES	(-)	Total (club) wage bill.
EMPLOY	(?)	Total number of club employees.
TENURE25	(+)	Average managerial tenure at the club over the last 25 seasons.
TENURE10	(+)	Average managerial tenure at the club over the last 10 seasons.

[a] In relation to managerial *in*efficiency.
[b] See Table 5.1 for details.

The factors influencing efficiency are grouped into three categories. The first contains variables on the manager's playing career. LEAGAPP and CLUBSP capture the length of the manager's playing career. LEAGAPP measures the total number of league games played, and CLUBSP measures the total number of clubs played for. These two variables are expected to account for the manager's prior knowledge of the game and prior knowledge of the procedures and conventions used by clubs[8]. Given that there is likely to be a quadratic relationship between LEAGAPP and efficiency, the variable LEAGAPP2 is also included. Generally, a negative sign on the coefficient refers to a fall in managerial inefficiency or a rise in managerial efficiency[9]. Prior parameter expectations suggest both LEAGAPP and CLUBSP will be negatively related to managerial inefficiency (that is, an increase in LEAGAPP or CLUBSP is expected to lead to a fall in managerial inefficiency), whereas LEAGAPP2 should be positively related to managerial inefficiency.

We contend that knowledge gained as a player may be position-specific. In football there are four main playing positions: goalkeeper, defender, midfielder and forward[10]. It is likely that some positions (e.g., defenders and midfielders) lend themselves more to the strategic side of the game. Thus, defenders and midfield players are likely to have a greater appreciation and deeper understanding of formations and tactics. The interactive nature of the game does, however, suggest that these effects will not be as far-reaching as they are in more individualistic sports such as baseball.

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[8] CLUBSP may also capture the attitude of the manager. For example loyal servants will have only played for one or two clubs whilst capricious stars usually find it difficult to settle at any one club.
[9] Most of the following variables are described in terms of the effect on managerial *in*efficiency in order to standardise the discussions here with the inefficiency effects model.
[10] Sometimes players do not neatly fall into one particular category because they can play in a variety of positions.

Nevertheless, playing position is modelled using four dummy variables: GOALKEEP, DEFENDER, MIDFIELD, and FORWARD[11].

Another possibility is "good" players make "good" managers due to innate ability. This is based on the philosophy that managers who have achieved at the highest level during their playing careers should find it easier to motivate and inspire players[12]. The quality of the manager's playing career has not been previously analysed in efficiency studies, but has been analysed elsewhere (e.g., in hazard models[13] and career decision models[14]). Here we employ total number of international appearances (CAPS) and total number of under-21 and under-23 international appearances (U2123) to measure the quality of the manager's playing career[15].

The second category of factors relate to managerial experience to date (managerial longevity)[16]. As with the playing experience measures we wish to account for both the quantity and quality of managerial experience. We employ number of clubs managed prior to this appointment (CLUBSM)[17] and total months managing before this job (MMBTJ) to account for the quantity of managerial experience. A priori both should be negatively related to managerial inefficiency. The relevance of managerial experience is captured in the division experience variable (MMDIVIN). This variable measures the

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[11] Whether the manager was a club captain is likely to proxy for innate leadership qualities. Unfortunately we were unable to acquire data on this variable.
[12] Singell (1991) notes however that the top players in baseball do not usually become managers.
[13] Audas *et al.* (2000).
[14] Singell (1991).
[15] In preliminary estimations we also considered divisional distribution of appearances and playing honours (e.g., championship medals and cup medals). These were subsequently dropped from the analysis due to consistently poor levels of statistical significance.
[16] Recall that managers have little or no formal educational qualifications. Many present day managers will, however, have undertaken job-market training in the form of coaching courses run by the Football Association. We were unable to acquire data on this variable. Even so, we are confident, for football managers at least, that actual labour market experience is more important than the number of qualifications gained.
[17] This measure may also capture the frequency with which a manager has his employment terminated.

total months managing in the current division and is expected to be negatively related to inefficiency. As before, we envisage possible quadratic relationships between MMBTJ and inefficiency (MMBTJ2), and MMDIVIN and inefficiency (MMDIVIN2).

The above variables relate to the manager's general labour market experiences. To accommodate specific managerial experience (job tenure) we employ the total number of months managing the current club and the square of the total number of months managing the current club (MMCC and MMCC2). Previous work has found that the longer a manager remains with a particular club the higher is his efficiency (Porter and Scully, 1982). We expect these job tenure variables to exert a much stronger (negative) effect on managerial inefficiency compared to the general managerial experience variables.

The general and specific experience variables suggest there is a managerial learning curve: as the manager's experience increases so too does his efficiency. The rate at which he learns may be dependent on whether the manager has had some kind of prior affiliation with the current club either as a player (PLAYCLUB), as an assistant manager or coach (CHASCLUB), or in a previous spell as manager (PREVSPEL). Each of these prior affiliation variables are incorporated as dummy dichotomous variables. A dummy variable for whether the manager is also contracted as a player at the club and played at least one game during the season in question (PLAYMAN), is used to account for any possible conflicts in responsibility and loyalty. Such conflicts arise because player-managers often have the difficult decision of dropping players that are also teammates. In addition, the dual role often means that the manager is unable to devote enough attention to managing the club. PLAYCLUB, CHASCLUB and PREVSPEL are all expected to be negatively related to inefficiency, PLAYMAN is expected to be positively related to inefficiency.

Any life-cycle effects which have not been picked up by the previous measures will be contained in the age variables MANAGE and MANAGE2. There are no prior parameter expectation for these two variables, although in accordance with the frequently observed concave age-productivity profile it is most likely that MANAGE will be negative and MANAGE2 will be positive.

All of the above measures relate to the quality (ability) of the manager (q_{it}^{M}). The third and final category of factors are those that relate to the characteristics of the club (e_{it}^{M}). Principally these measures are included to test some of the agency and incentive effects discussed in Chapter 1 and hypothesised to football managers in Chapter 4. Firstly, the size of the firm has been found to be an important factor influencing efficiency (Lundvall and Battese, 1998). A priori we might expect the total number of club employees (EMPLOY) to be negatively related to inefficiency (i.e., an increase in club size reduces managerial inefficiency) because managers of larger clubs will have more assistants, coaches and "backroom" staff to delegate responsibility to. Thus, in larger clubs the manager is solely concerned with the playing side of the business. On the other hand, the higher efficiency brought about through concentrating on specific tasks has to be weighed against the *fait accompli* that individuals in large firms have a greater incentive to shirk. But since the monitoring process in football is transparent irrespective of club size, we expect EMPLOY to be negatively related to inefficiency.

A second measure, WAGES, examines the impact of the total wage bill of the club. Because wage data includes both the wage paid to the players and the manager –

see equation (4.5) - a negative relationship with inefficiency is indicative of either incentive payments or efficiency wages for the players or manager. There is much anecdotal evidence to suggest that incentive systems are implicitly used in players' contracts, but much less so for managers. Recently, there has been talk of introducing results-related incentives into managerial contracts (Daily Telegraph, 17 February 1998), but the millions of pounds currently coming into football continues to be spent mostly on players rather than on managers.

To complete this section, two average tenure variables (TENURE25 and TENURE10) are included to account for the club's history of managerial turnover. Some clubs (e.g., Crewe, Port Vale, Wimbledon and Wrexham) change their manager less often than others (e.g., Manchester City, Notts County and Southend). Clubs who are less prone to change[18] may find that the manager exerts less than full effort, although as with all the incentive effects, the extent to which this is possible depends on the adequacy of the monitoring process. Assuming the monitoring process is not perfect, these two variables are expected to be positively related to managerial inefficiency[19].

Finally, a time trend (TIME) is included to analyse the structure of inefficiency over time. This variable determines whether, over time, managers move nearer to or further away from the production frontier. If the time trend is positive managerial inefficiency increases over time, if it is negative it decreases. At one level we might expect this variable to be negative, reflecting the improvements brought about by greater managerial experience (i.e., managerial learning curve). Alternatively, a positive effect might represent the increasing commercial pressures put upon managers particularly at

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[18] Possibly because of the disruptive effect which usually follows managerial succession. We discuss this further when we talk about whether the manager makes a difference.
[19] External circumstances are also important (i.e. the ease with which a new job can be obtained).

those clubs that have sought stock market listings. The frequency with which managers are replaced may be another factor. Apart from anything else, the changing ownership structure in professional football (Table 3.1) is leading to a greater degree of governance and accountability for all members employed by the football club[20]. One consequence of this is the proliferation of managerial turnover.

Table 7.2 presents summary statistics for the managerial and club characteristics by individual division and for the pooled sample. Although not recorded in the table, the data revealed, as expected, that the majority of managers (96 per cent) were previously players. According to the table the playing position of most of these managers was as a defender or a midfielder[21]. Taken together, these two position categories account for approximately two-thirds of all observations. Both LEAGAPP and CLUBSP variables are relatively stable across division; the average manager made a total of approximately 400 league appearances for four to five clubs. While there is little variation in the quantity of playing experience by division, the quality of experienced gained is division specific. For example, the average number of international caps is 20 for managers in the Premier League while it is only six for managers operating in Division 3[22].

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[20] We did consider measuring the impact of stock market placing on subsequent managerial efficiency, but club listings on the various markets has been a very recent phenomenon whose impact has yet to be established.

[21] Interestingly, the number of forwards is highest and the number of defenders is lowest in the Premier League. The dominance, or otherwise, of certain positional categories may reflect team composition and style of play within these divisions.

[22] Both international appearances and goal-scoring record account for much of the difference in the predicted valuations of the playing resources (see Appendix II).

Table 7.2 Descriptive Statistics: Managerial Inefficiency Effects

	Division[a]				
Variable	Premier League	Division 1	Division 2	Division 3	All Divisions
MANAGE	46.021	43.441	43.816	41.685	43.661
	(5.456)	(6.548)	(5.965)	(6.258)	(6.268)
LEAGAPP	385.796	405.066	370.366	406.560	392.551
	(183.485)	(182.619)	(201.222)	(184.593)	(188.257)
CLUBSP	4.116	4.593	4.939	4.952	4.664
	(2.244)	(2.395)	(2.403)	(2.466)	(2.400)
CAPS	19.918	12.582	13.451	6.417	12.862
	(29.185)	(21.815)	(27.989)	(17.517)	(24.735)
U2123	2.395	1.714	0.927	0.935	1.472
	(3.451)	(3.207)	(2.478)	(2.275)	(2.938)
PLAYMAN	0.102	0.132	0.091	0.179	0.127
MMBTJ	63.347	52.077	32.872	24.708	42.862
	(67.749)	(64.362)	(45.686)	(43.176)	(58.001)
CLUBSM	1.864	1.379	1.165	0.845	1.298
	(1.777)	(1.557)	(1.398)	(1.262)	(1.542)
MMDIVIN	44.333	28.005	18.433	14.167	25.744
	(48.909)	(31.049)	(20.096)	(18.810)	(33.295)
MMCC	24.503	20.714	21.018	9.571	18.800
	(32.979)	(31.865)	(27.811)	(15.921)	(28.379)
CHASCLUB	0.245	0.258	0.207	0.173	0.221
PLAYCLUB	0.422	0.418	0.244	0.387	0.368
PREVSPEL	0.048	0.088	0.055	0.065	0.065
GOALKEEP	0.027	0.011	0.067	0.060	0.041
DEFENDER	0.231	0.357	0.323	0.399	0.331
MIDFIELD	0.388	0.319	0.311	0.333	0.336
FORWARD	0.333	0.258	0.238	0.179	0.250
WAGES[b]	6,559,417	2,810,064	1,293,437	761,188	2,994,364
	(3,843,876)	(1,590,676)	(594,284)	(291,881)	(3,103,584)
EMPLOY[c]	132.19	97.409	67.222	50.528	91.549
	(52.412)	(34.278)	(22.738)	(11.199)	(46.588)
TENURE25	3.978	3.453	2.785	2.426	3.143
	(1.988)	(2.728)	(0.910)	(1.864)	(2.084)
TENURE10	3.143	3.889	3.447	2.494	3.492
	(1.494)	(2.671)	(2.260)	(1.418)	(2.347)

Note: Standard deviations in parentheses (except for dummy variables).
[a] Unless otherwise stated, N = 147 for Premier League; 182 for Division 1; 164 for Division 2; 168 for Division 3; and 661 when all four divisions are pooled.
[b] N = 118 (Premier); 133 (Division 1); 120 (Division 2); 86 (Division 3); and 457 (all divisions).
[c] N = 119 (Premier); 127 (Division 1); 108 (Division 2); 72 (Division 3); and 426 (all divisions).

The average level of managerial experience prior to the current appointment also varies by division: about six years for Premier League managers, four years for Division 1 managers, and slightly less than three years and two years for managers in Divisions 2 and 3, respectively. The mean number of months the manager has been managing his current club is about 18 months. However, there are a significant number of outliers here, resulting in a skewed distribution. This is confirmed by a median level of months managing of nine months[23]. Such findings are compatible with the view that the hazard rate (i.e., the probability of job separation) is highest in the early part of the job, but decreases as tenure increases (Audas *et al.* 2000[24]). The sample distribution here indicates that few managers remain with the same club for more than three seasons.

In general, the managerial variables suggest that the more experienced managers manage in the top division and the least experienced manage in the lower divisions. For instance, the most inexperienced managers are player-managers and we find that nearly 40 per cent of the player-managers are based in Division 3[25]. The positive distribution of managerial experience between divisions (i.e., higher the division, the greater the level of managerial experience) is reminiscent of an internal labour market (Doeringer and Piore, 1971): managers are initially allocated to clubs in lower divisions in order to gain job market experience. As experience increases an internal promotion occurs and the manager progressively moves up division(s) (vertical movement). The vertical movement is, naturally, conditional on success. If at any time the manager is unsuccessful there may be a sideways (horizontal) movement, or, in extreme cases, demotion. This implicit sorting arrangement has certain parallels with the notion that the

[23] Median values available from the author on request.
[24] See, in addition, Chapman and Southwick (1991) for an application to American baseball.
[25] Calculated by multiplying sample mean by sample size.

football industry is made up of one multi-divisional (M-form) firm rather than a collection of smaller fragmented units[26].

Many managers have had a prior affiliation with the current club, usually as a player, coach or assistant manager. Clubs are, however, very reluctant to re-appoint previous managers, although there are some notable exceptions (e.g., Steve Coppell has had three separate spells managing Crystal Palace). Our evidence indicates that only 6.5 per cent of all posts involve re-appointments. In contrast, 22 per cent of appointments involve managers who were once a coach or assistant manager at the club[27] and 37 per cent of managers once played for the current club.

The firm-specific measures WAGES and EMPLOY vary directly with division. The average Premier League club has a wage bill of £6.6 million and employs around 132 people (about one-third of which are players). The figures for the average Division 3 club are £0.8 million and 50, respectively. Tenure, however, is inversely related to division. The evidence here suggests that tenure levels in the last 10 years have become slightly longer compared with tenure levels over the last 25 years[28].

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[26] McMaster (1997) first suggested the idea of the football industry resembling an M-form structure. Essentially each club operates as a quasi-firm with the governing bodies (the Football League and the Premier League) having overall responsibility.

[27] In many instances this is because the club has promoted from within.

[28] An increase in job terminations has, however, occurred since the inception of the Premier League. The average number of terminations for seasons 1992/93 to 1997/98 is 43.5 (see Table 3.7), nearly six terminations higher than the average for seasons 1972/73 to 1991/92 inclusive (See, Table 1, Audas *et al.*, 2000).

7.4 Results

The first set of results (see Table 7.3) focus on the role played by the human capital experience measures. We compare the sign and significance of twelve human capital managerial inefficiency effects for five different input-output specifications. The production and variance parameter estimates are detailed elsewhere (Table 6.7). Even though likelihood ratio tests (Table 6.8) points to WINVALUE as being the preferred model, the other models produce some interesting results and are therefore included for comparative purposes[29].

Before comparing the inefficiency effects it is important to consider the interpretation of the estimated coefficients. Recall from Section 7.3 that a negative sign on the coefficient refers to a *fall* in managerial *in*efficiency. We assume a linear functional form between managerial efficiency and the managerial inefficiency effects. However, and in contrast to studies that adopt a two-stage procedure, the interpretation of the coefficients in the simultaneous estimation procedure is not straightforward. This is because the values relate to the way the managerial specific factors shift the mean of the (pre-truncated) distribution of U_{it} (Coelli, 1996b). Consequently the values tend to be quite small[30].

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[29] The results presented here are little changed if we enter other inefficiency effects too. We formally introduce these other effects (including club-specific factors) later on (Table 7.4 onwards) to enable us to develop the model heuristically.

[30] Coelli (1996b) notes that in order to quantify the specific contribution of each of the inefficiency effects it is necessary to derive the partial derivatives of the efficiency predictor with respect to each of the inefficiency effects. No study to date has done this. In common with other studies we focus on the sign and significance of the effect.

Table 7.3 Managerial Inefficiency Effects by Model Specification: Human Capital Measures

Variable	Parameter	Model Specification WIN VALUE	WIN RAW	WIN WAGE	POINTS VALUE	NEWPOINTS VALUE
CONSTANT	δ_0	-9.697	-13.185	-10.027	-5.820	-4.538
		(-2.739)	(-2.775)	(-2.435)	(-1.844)	(-2.306)
MANAGE	δ_1	0.111	0.180	0.106	0.065	0.047
		(2.821)	(3.120)	(2.529)	(2.076)	(2.456)
LEAGAPP	δ_2	0.0005	0.0005	-0.0007	-0.0002	-0.0005
		(1.249)	(1.831)	(-1.813)	(-0.814)	(-2.286)
CAPS	δ_3	-0.033	-0.029	-0.022	-0.024	-0.020
		(-2.526)	(-2.256)	(-2.600)	(-1.803)	(-2.278)
U2123	δ_4	0.036	0.028	0.092	0.087	0.097
		(2.290)	(1.356)	(2.744)	(2.621)	(2.940)
PLAYMAN	δ_5	-0.216	1.658	-1.524	0.594	0.722
		(-0.752)	(3.129)	(-2.321)	(1.815)	(2.238)
MMDIVIN	δ_6	0.014	0.021	0.015	0.012	0.013
		(4.237)	(2.918)	(3.210)	(2.749)	(2.971)
MMCC	δ_7	-0.334	-0.032	-0.054	-0.018	-0.016
		(-2.990)	(-2.690)	(-2.842)	(-2.202)	(-2.729)
CLUBSM	δ_8	-0.150	-0.547	-0.340	-0.187	-0.227
		(-2.340)	(-2.839)	(2.712)	(-2.206)	(-2.593)
CHASCLUB	δ_9	0.469	0.860	0.284	-0.003	-0.225
		(2.551)	(2.789)	(1.424)	(-0.026)	(-1.647)
PLAYCLUB	δ_{10}	-0.888	-0.952	-0.277	-0.892	-0.820
		(-3.183)	(-2.683)	(-1.553)	(-2.043)	(-2.474)
PREVSPEL	δ_{11}	-0.879	-0.011	-0.779	-1.156	-1.143
		(2.369)	(-0.043)	(-1.694)	(-1.796)	(-2.196)
TIME	δ_{12}	0.306	0.218	0.548	0.146	0.096
		(2.735)	(2.895)	(2.964)	(1.434)	(1.830)

Note: Based on BC2 (1995). We did compare the performance of the above simultaneous estimation model with the traditional two-stage approach using BC (1992). To make meaningful comparisons the negative of the logged efficiency scores is regressed on the above human capital measures. In all but one case (PLAYMAN) the signs of the coefficients were the same. However, only MANAGE and TIME (as expected) were statistically significant.

Overall, nine of the human capital inefficiency effects have the same sign in each of the five models. In the WINVALUE specification, ten of the variables are statistically significant at the 10 per cent level or better. However, the signs of LEAGAPP, U2123, MMDIVIN and CHASCLUB are opposite to that expected. All four have positive coefficients which suggest that these variables act to increase inefficiency (reduce efficiency). The positive contribution of LEAGAPP may be the result of the manager extending his playing career too long, possibly including some of the PLAYMAN effects.

It could also be that good players become managers much sooner than average players. The positive impact of U2123 suggests those managers that did not realise their potential as a player will be less successful managerially (a high number of U2123 appearances tends to mean a small number of full international appearances). Similarly, the positive contribution of CHASCLUB may indicate that the person was previously not considered good enough to manage the club. For the club to subsequently appoint him as manager may be interpreted to mean that there was no-one else available (i.e., "he was the club's last resort"). Rather intriguingly, there seems to be no plausible reason why MMDIVIN should be positively related to managerial inefficiency. Finally, the negative sign for PLAYMAN is also unexpected but is not significantly different from zero.

Generally, the managerial experience variables perform better than the playing experience variables. The average t-statistic for the playing experience variables is 2.312 compared to an average of 2.897 for the managerial experience variables. These findings contrast with the previously held view that initial experience matters most (Singell, 1993). As expected, specific managerial experience has a greater impact than general managerial experience.

The sign of almost all of the variables are unaltered under the WINRAW specification. This is not surprising given that WINRAW is essentially a robustness test for the VALUE measure, although it is gratifying to also see similarities in the sizes of these coefficients. The one exception is the PLAYMAN variable, which not only changes sign (from negative to positive) but is now highly significant (better than the 1 per cent level).

Replacing VALUE as the input variable with WAGE has the effect of increasing the statistical significance of the player characteristics variables with LEAGAPP now "correctly" signed, but the overall significance of the managerial experience variables is reduced.

The most dramatic change to the results occurs when the output measure is altered. For the POINTSVALUE specification only six of the coefficients are now statistically significant at the 10 per cent level or better. When NEWPOINTS is used to measure output this number increases to 11 even though the sign and magnitude of the coefficients are little changed. In addition, three variables (LEAGAPP, PLAYMAN and CHASCLUB) are now "correctly" signed. Although the NEWPOINTSVALUE specification produces better results (in terms of sign and significance) than the WINVALUE specification, likelihood ratio tests (Table 6.8) suggest that the inefficiency effects are equal to zero in the NEWPOINTSVALUE model. Therefore, on the basis of statistical testing we now extend the analysis using WINVALUE.

The 12 inefficiency effects discussed above represent a parsimonious set of variables. We now augment the number of inefficiency effects to include playing position dummies, quadratic terms and, more importantly, club-specific variables. The results of this exercise are reported in Table 7.4. In MODEL 1 we include CLUBSP and MMBTJ to complement LEAGAPP and CLUBSM entered in the parsimonious model. Four positional dummies are also included. MODEL 2 comprises all the variables entered in MODEL 1 (with the exception of the position dummies) plus five quadratic terms. The four club-specific variables together with the variables entered in MODEL 2 (minus the quadratic effects) constitute MODEL 3. Finally, in MODEL 4 we enter all of the aforementioned variables.

Table 7.4 Inefficiency Effects: Playing Career, Managerial Experience and Club-Specific Effects

		Model Specification (WINVALUE)			
Inefficiency Effects	Parameter	MODEL 1	MODEL 2	MODEL 3	MODEL 4
CONSTANT	δ_0	-7.651 (-2.791)	13.143 (2.426)	-6.816 (-2.896)	14.209 (2.556)
MANAGE	δ_1	0.091 (2.703)	-0.792 (-2.567)	0.084 (2.921)	-0.782 (-2.616)
LEAGAPP	δ_2	0.001 (2.273)	-0.188 (-1.763)	0.001 (2.147)	0.0002 (0.168)
CLUBSP	δ_3	-0.086 (-2.993)	-0.082 (-2.369)	-0.116 (-3.283)	-0.077 (-2.080)
CAPS	δ_4	-0.033 (-2.911)	-0.030 (-2.719)	-0.034 (-2.942)	-0.026 (-2.922)
U2123	δ_5	0.049 (2.812)	0.028 (1.446)	0.069 (3.185)	0.043 (2.002)
MMBTJ	δ_6	-0.003 (-1.574)	0.031 (3.004)	-0.003 (-1.523)	0.030 (3.136)
CLUBSM	δ_7	-0.036 (-0.567)	-0.032 (-0.471)	-0.048 (-0.750)	-0.029 (-0.417)
PLAYMAN	δ_8	-0.153 (-0.488)	-0.346 (-1.005)	-0.135 (-0.508)	-0.587 (-1.548)
MMDIVIN	δ_9	0.016 (3.717)	0.021 (2.961)	0.014 (3.980)	0.021 (3.028)
MMCC	δ_{10}	-0.039 (3.079)	-0.048 (-3.165)	-0.037 (-3.446)	-0.053 (-3.343)
CHASCLUB	δ_{11}	0.552 (2.580)	0.558 (2.542)	0.265 (1.598)	0.360 (1.659)
PLAYCLUB	δ_{12}	-0.816 (-3.219)	-0.676 (2.838)	-0.933 (-3.100)	-0.582 (-2.411)
PREVSPEL	δ_{13}	-0.714 (-1.954)	-1.309 (-2.925)	-0.735 (-2.455)	-1.018 (-2.316)
GOALKEEP	δ_{14}	-0.683 (-1.098)			0.131 (0.202)
DEFENDER	δ_{15}	-0.945 (-1.796)			-0.366 (-0.708)
MIDFIELD	δ_{16}	-1.121 (-1.858)			-0.887 (-1.434)
FORWARD	δ_{17}	-0.960 (-1.842)			-0.853 (-1.428)

Table 7.4 - *Continued*

Inefficiency Effects	Parameter	MODEL 1	MODEL 2	MODEL 3	MODEL 4
MANAGE2	δ_{18}		0.009 (2.656)		0.009 (2.678)
LEAGAPP2	δ_{19}		0.373×10^{-5} (2.151)		0.428×10^{-6} (0.307)
MMDIVIN2	δ_{20}		0.137×10^{-4} (0.520)		0.227×10^{-4} (0.811)
MMBTJ2	δ_{21}		-0.189×10^{-3} (-3.098)		-0.185×10^{-3} (-3.284)
MMCC2	δ_{22}		0.115×10^{-3} (2.425)		0.117×10^{-3} (2.495)
WAGES	δ_{23}			-0.635 (-2.960)	-0.468 (-1.857)
EMPLOY	δ_{24}			-0.834 (-2.279)	-0.663 (-1.900)
TENURE25	δ_{25}			0.097 (2.749)	0.080 (2.512)
TENURE10	δ_{26}			0.118 (2.557)	0.110 (2.328)
TIME	δ_{27}	0.296 (2.851)	0.284 (3.168)	0.271 (3.184)	0.277 (3.150)

Notes: N = 661. Given the gaps in the observations for WAGES and EMPLOY suitable estimates were used. These proved equally robust to a specification which included only observed values. Both WAGES and EMPLOY are calculated as mean deviations.

MODEL 1 = WINVALUE inefficiency effects plus CLUBSP, MMBTJ and playing position dummies; MODEL 2 = MODEL 1 inefficiency effects (except position dummies) plus playing and managerial quadratics; MODEL 3 = MODEL 2 inefficiency effects (except quadratics) plus firm-specific effects; MODEL 4 = All inefficiency effects.

The results are little changed when MMBTJ or CLUBS are excluded.

In MODEL 1, CLUBSP is negative and statistically significant at the 1 per cent level. Its inclusion has the effect of increasing the statistical significance (to the 5 per cent level) of LEAGAPP, although the coefficient remains positive. In contrast, including MMBTJ has the effect of reducing the significance of CLUBSM to the extent that CLUBSM is no longer statistically significant. This suggests that there is a high degree of co-linearity between these two variables[31]. Each of the playing position dummies is negatively signed and only GOALKEEP is insignificant at the 10 per cent level. The relative magnitudes and significance levels of these four coefficients suggest that midfield players make better managers. The sign, significance and magnitude of the other human capital effects are similar to before.

Four out of five quadratic terms in MODEL 2 are statistically significant at the 5 per cent level or better, and, as expected, all are positive except for MMBTJ2. This indicates that managerial efficiency increases at a decreasing rate with respect to both playing and managerial experience. Thus, there is some support for the commonly observed concave age-performance profile.

In an attempt to explain the relationship between managerial effort (incentives) and managerial efficiency we include four club-specific factors as inefficiency effects (MODELS 3 and 4). A more common approach has been to compare wage equations with performance equations (e.g., Medoff and Abraham, 1980; Medoff and Abraham, 1981) or to enter productivity measures in wage equations (Holzer, 1990). The purpose in each case is to demonstrate whether experience is related to performance or wages. Here, we enter WAGES, EMPLOY, TENURE25 and TENURE10 as additional managerial inefficiency effects.

[31] This does not seriously alter the findings on the other variables (see WINVALUE, Table 7.3).

In MODELS 3 and 4 each of the four club-specific factors are statistically significant at the 10 per cent level or better. The variable WAGES is negative and implies that the absolute level of wages paid relative to the average (for that division) has the effect of reducing managerial inefficiency. This is consistent with the notion that higher wages induce higher levels of performance. But we are not able to say whether incentive pay is used in determining managerial remuneration. More realistically perhaps, the effect of the wage variable may be the result of inducements given to the playing resources, so that what appears to be an improvement in managerial efficiency is actually an improvement in the effort levels of the players.

The negative value for EMPLOY suggests that managerial inefficiency decreases as the relative club size increases. This implies that the managers at larger clubs are able to concentrate exclusively on the playing side of the business. It also suggests that there are few incentive problems in relation to club size. In contrast, the positive values for both tenure measures indicate that managers at clubs with high average tenure levels are generally less efficient than those managers who are employed by clubs where the threat of dismissal is higher. Here incentives do seem to be playing an important role.

Further examination of MODEL 3 and MODEL 4 also reveals that the club-specific effects have minimal impact on the human capital measures. That is, the magnitude, sign and significance of the human capital variables are little changed when the club-specific measures are included. More precisely, this means that both experience and incentives influence managerial efficiency. The importance of this conclusion cannot be understated. Club-specific factors do influence the efficiency of the manager. In sum, the significance of both TENURE measures and the WAGES variable suggest the monitoring system in the football industry is imperfect[32]; there is potential for managerial shirking.

In order to ascertain more precisely the impact of the human capital factors and the club-specific factors we estimated MODEL 4 (with 26 of the 27 variables[33]) for each division separately (see Table 7.5). For Premier League managers, only four of the inefficiency effects have signs opposite to those reported in MODEL 4. But the t-statistics are much lower (on average, 25 per cent lower). An even greater disparity exists between the full sample and the other divisions. For Division 1 managers, none of the playing experience measures are significant at the 10 per cent level or better and, although WAGES is statistically significant, it is now positively signed. The downward trend in significance levels continues into Divisions 2 and 3 where, respectively, only three and two inefficiency effects are significant at the 10 per cent level or better. In both cases, the significant variables are dominated by club-specific factors.

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[32] Evidence that the monitoring system in football is imperfect is also provided by the commonly observed "tandem effect" – players and managers moving together (i.e., when a manager moves to another club he often takes with him some players from his previous club(s)).

[33] GOALKEEPER position dummy was dropped.

Table 7.5 Managerial Inefficiency Effects by Division (MODEL 4)

Variable	Parameter	Division			
		Premier League	Division 1	Division 2	Division 3
CONSTANT	δ_0	-1.818 (1.112)	2.883 (0.843)	1.192 (0.695)	0.151 (0.152)
MANAGE	δ_1	-0.116 (-1.138)	-0.141 (-0.795)	0.030 (0.436)	-0.016 (-0.220)
LEAGAPP	δ_2	0.003 (1.217)	0.002 (0.972)	-0.001 (-0.641)	0.838×10^{-3} (0.331)
CLUBSP	δ_3	-0.222 (-2.174)	0.028 (0.435)	-0.016 (-0.245)	0.015 (0.292)
CAPS	δ_4	-0.021 (-2.292)	-0.003 (-0.430)	-0.002 (-0.274)	-0.004 (-0.613)
U2123	δ_5	0.034 (0.890)	-0.018 (-0.608)	0.086 (1.581)	-0.049 (1.104)
MMBTJ	δ_6	0.016 (2.420)	0.009 (1.652)	0.013 (0.996)	0.010 (1.128)
CLUBSM	δ_7	0.135 (1.026)	0.175 (0.987)	-0.167 (-0.902)	-0.026 (-0.169)
PLAYMAN	δ_8	1.273 (1.426)	-0.311 (-0.571)	0.348 (0.881)	0.065 (0.188)
MMDIVIN	δ_9	0.032 (1.977)	0.016 (0.792)	0.036 (1.637)	0.007 (0.472)
MMCC	δ_{10}	-0.025 (-1.574)	-0.004 (-0.479)	-0.055 (-2.304)	-0.002 (-0.105)
CHASCLUB	δ_{11}	0.117 (0.258)	1.283 (1.838)	-0.550 (-1.355)	-0.091 (-0.276)
PLAYCLUB	δ_{12}	-0.266 (-0.630)	-0.484 (-1.894)	-0.547 (-1.388)	0.063 (0.298)
PREVSPEL	δ_{13}	-1.110 (-1.220)	-1.159 (-1.859)	0.200 (0.268)	-0.040 (-0.085)
DEFENDER	δ_{14}	-0.175 (-0.306)	-0.629 (-0.834)	-0.474 (-0.962)	-0.223 (-0.432)
MIDFIELD	δ_{15}	-1.023 (-1.443)	-0.835 (-0.881)	-0.925 (-1.390)	-0.143 (-0.257)
FORWARD	δ_{16}	-0.950 (-1.343)	-0.745 (-1.102)	-0.314 (-0.648)	-0.405 (-0.703)
MANAGE2	δ_{17}	0.544×10^{-3} (0.388)	0.001 (0.660)	-0.501×10^{-3} (-0.582)	0.296×10^{-3} (0.306)
LEAGAPP2	δ_{18}	-0.232×10^{-5} (-0.776)	-0.281×10^{-5} (-1.149)	0.865×10^{-6} (0.366)	-0.871×10^{-6} (-0.319)
MMDIVIN2	δ_{19}	-0.971×10^{-4} (-1.331)	-0.126×10^{-3} (-0.733)	0.113×10^{-3} (0.628)	-0.145×10^{-3} (-0.767)
MMBTJ2	δ_{20}	-0.966×10^{-4} (-2.546)	-0.572×10^{-4} (-2.397)	-0.122×10^{-3} (-1.560)	-0.415×10^{-4} (-1.047)
MMCC2	δ_{21}	0.924×10^{-4} (1.067)	-0.870×10^{-5} (-0.143)	0.112×10^{-3} (1.062)	-0.156×10^{-3} (-0.867)
WAGES	δ_{22}	-2.223 (-2.541)	0.793 (2.831)	0.164 (0.586)	-0.683 (-1.986)
EMPLOY	δ_{23}	1.304 (1.608)	-0.395 (-1.180)	-1.545 (-1.759)	0.398 (0.812)
TENURE25	δ_{24}	0.165 (1.874)	0.146 (1.480)	-0.251 (-1.394)	-0.145 (-0.936)
TENURE10	δ_{25}	0.080 (1.123)	-0.235 (-1.306)	0.197 (1.720)	0.198 (1.679)
TIME	δ_{26}	0.382 (2.932)	-0.026 (-0.343)	0.092 (1.231)	-0.007 (-0.080)
N		147	182	164	168

Note: Asymptotic t-values in parentheses.

The most likely reason for the general insignificance of the variables is the relatively low number of observations (26 variables and only 140–180 observations), compared with the estimations for the full sample. Notwithstanding this difficulty it is interesting to note that the club-specific measures are typically more important than human capital factors in each division. One possible reason for this is that the WAGE variable proxies for the human capital variables[34]. To test this we replicated the analysis outlined in Table 7.5 for the human capital measures only[35]. The findings were more favourable for Premier League and Division 2 managers, in that the human capital coefficients were more significant, but little different for managers operating in Divisions 1 and 3[36].

The positive effect of the variable TIME is of particular concern. It suggests that managerial efficiency tends to decrease over time. A probable reason for this is the increasing pressures bestowed upon managers in the modern era. Club owners are often only too willing to change the manager following a poor run of results and even though displacement from one club is quickly followed by appointment at another club, managers need time to adjust to their new surroundings[37].

In order to evaluate more precisely individual efficiency over time we analysed the 27 managers that have been observed in every season of our sample. The managers were divided into the number of clubs they have managed during the sample period. This ranged from one to four. Figures 7.1 (a) – 7.1 (d) illustrates the results.

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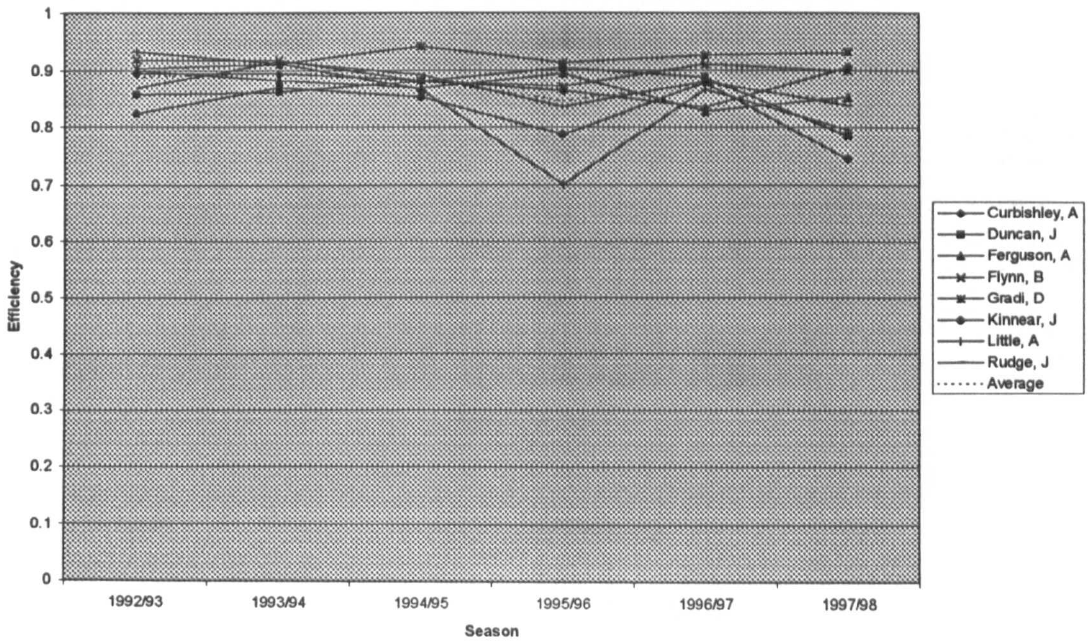
[34] For details, see Chapter 1. As this is more likely to be a player effect it could suggest that incentives for the players are more important than the manager per se.

[35] Available from the author on request.

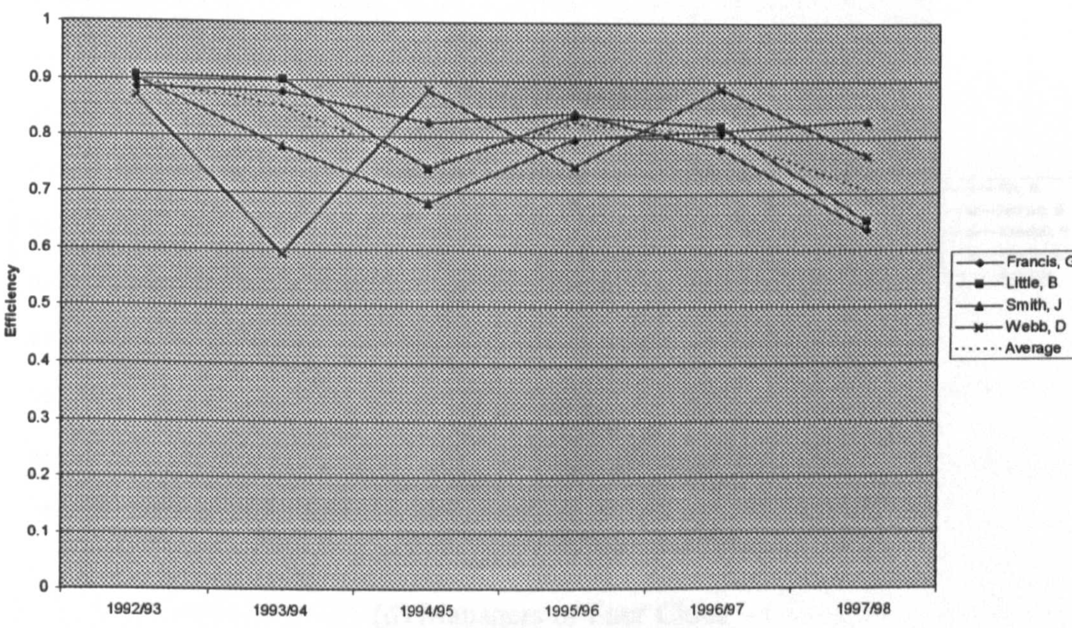
[36] Two other possibilities remain. Firstly, the difference between the divisions is a consequence of the levels of managerial turnover which acts as a disruptive effect (see Section 7.5). Recall that turnover is generally highest in Divisions 1 and 3, and lowest in the Premier League and Divisions 2. Secondly, the general insignificance of the results by division perhaps confirms our earlier thoughts on the divisional distribution of managers by experience. If similar managers are operating in each division then any difference in efficiency must, by definition, be explained by club-specific factors.

[37] These findings were confirmed when we re-estimated the model for "full" season observations only (N = 441) and found the time variable to be insignificant. We believe, therefore, that TIME is picking up succession effects.

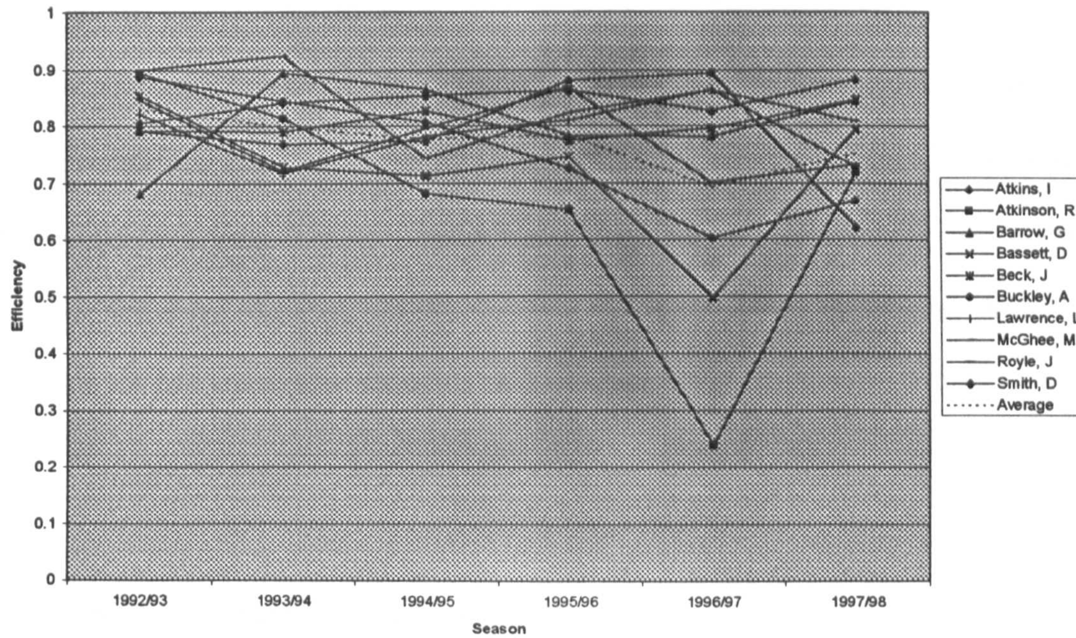
<u>Figure 7.1 Managerial Efficiency Over Time[a]</u>



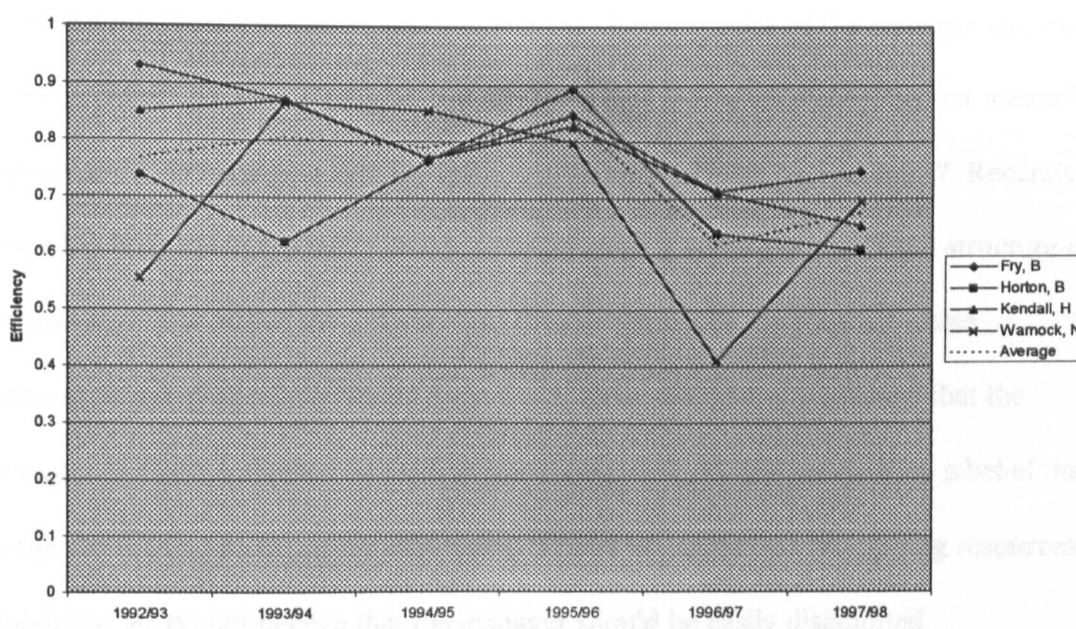
(a) Managers of One Club



(b) Managers of Two Clubs



(c) Managers of Three Clubs



(d) Managers of Four Clubs

[a] Where a manager changes club mid-season we have averaged the two efficiency scores.

It is clear from the diagrams that there is far less fluctuation in efficiency for managers who remain at one club compared with those managers who have had several appointments. Furthermore, the efficiency scores of these managers are almost identical.

This suggests that the one-club managers have reached a "steady-state" level of performance – there is no tendency for efficiency to change because effort is constant and the manager's human capital is at a maximum. This is broadly consistent with the ideas presented in Figure 4.3. But it is also true that the managerial input is transferable; following a period of adjustment efficiency tends to return to levels previously obtained, although the speed of adjustment depends, amongst other things, on whether the manager has had some prior affiliation with the club.

7.5 Does the Manager Make a Difference?

Even though the above results indicate that the characteristics of the manager and club-specific factors both have a significant effect on managerial efficiency, does it matter? In other words, do managers actually make a difference to team performance? Recently there has been much academic debate as to whether it is the organisational structure or the manager that makes the difference to firm performance. In football, some commentators, particularly Stefan Syzmanski, have continuously stressed that the manager has little influence on team performance. In part, this stems from a belief that it is the players that make *all* the difference. Whilst we agree that the playing resources are important we do not believe that the manager should be easily discounted.

There are essentially two ways of addressing the question of whether the manager makes a difference. Firstly, we can compare the actual win ratio with the frontier win ratio. For example, consider the mean win ratio and mean efficiency score (see Table 6.1 and Table 6.9). If mean efficiency increased to 100 per cent (i.e., one) the mean win ratio would increase from 0.294 (about 11 wins in the Premier League and

13.5 wins in the Football League) to 0.370 (about 14 and 17 wins, respectively)[38]. This translates into a 20 per cent improvement in team performance. However, since no manager in our study achieves 100 per cent efficiency it is perhaps more appropriate to compare actual win ratio with the win ratio of the best-practice manager. The best practice manager achieved an efficiency score of 0.951[39]. This corresponds to an improvement of about two wins in the Premier League and three wins in the Football League. Although these improvements are not large they can make the difference between promotion and relegation. Significantly, two additional wins would have meant survival for six of the 10 clubs relegated at the end of the 1997/98 season. However, since the league is a zero sum game in the sense that one team's win is another team's loss not all managers can become successful in this way.

Turning to a more detailed look at the efficiency scores of individual managers, Table 7.6 ranks managers who were observed on at least three occasions during the sample period[40]. Not only is there considerable difference between the mean efficiency of the top and bottom managers (36 per cent), but managers at the most successful clubs are generally not the most efficient. Of the top ten managers, only Kevin Keegan at Newcastle and Lou Macari at Swindon won divisional titles. Alex Ferguson at Manchester United (the most successful club in our sample period with four Premier League titles) is ranked only sixteenth. Further evidence for this is provided in Table 7.7. It shows that some of the less fashionable clubs such as Crewe, Walsall and Wrexham have the most efficient managers. In contrast, the managers at Blackburn, Everton and Manchester City appear to have made poor use of their considerable resources. The

[38] Recall that efficiency has an output increasing definition.
[39] This was the Reading manager Jimmy Quinn for season 1994/95.
[40] For a full list of efficiency scores for each manager by season see Appendix II.

most efficient managers are therefore the ones who are able to keep a team in a division or gain promotion when the quality of the playing resources suggests otherwise.

Table 7.6 Mean Efficiency of Football Managers[a]

Rank	Manager	Clubs (seasons observed)	Number of Observations	Mean Efficiency
1	Nicholl, Chris	Walsall (3,4,5)	3	0.924
2	Gradi, Dario	Crewe (1,2,3,4,5,6)	6	0.921
3	Keegan, Kevin	Newcastle (1,2,3,4,5)	5	0.907
4	King, John	Tranmere (1,2,3,4)	4	0.904
5	McCarthy, Mick	Millwall (1,2,3,4)	4	0.903
6	Quinn, Jimmy[b]	Reading (3,4,5)	3	0.901
7	Flynn, Bryan	Wrexham (1,2,3,4,5,6)	6	0.899
8	Macari, Lou	Stoke (1,2,3,4,5)	5	0.891
9	Curbishley, Alan[c]	Charlton (1,2,3,4,5,6)	6	0.879
10	Jones, Dave	Stockport (4,5); Southampton (6)	3	0.878
=11	Sutton, Dave	Rochdale (1,2,3)	3	0.876
=11	O'Neill, Martin	Wycombe (2,3); Norwich (4); Leicester (4,5,6)	6	0.876
13	Rioch, Bruce	Bolton (1,2,3); Arsenal (4)	4	0.874
14	Burley, George	Colchester (3); Ipswich (3,4,5,6)	5	0.872
15	Rudge, John	Port Vale (1,2,3,4,5,6)	6	0.871
=16	Ferguson, Alex	Manchester United (1,2,3,4,5,6)	6	0.870
=16	Thompson, Steve	Lincoln (1); Southend (3); Notts County (4,5)	4	0.870
=18	Gregory, John	Wycombe Wanderers (5,6); Aston Villa (6)	3	0.864
=18	Wilson, Danny	Barnsley (3,4,5,6)	4	0.864
=20	Walsh, Mike	Bury (1,2,3)	3	0.863
=20	Ardiles, Osvaldo	West Bromwich Albion (1,2); Tottenham (3)	3	0.863
=22	Duncan, John	Chesterfield (1,2,3,4,5,6)	6	0.862
=22	Ratcliffe, Kevin	Chester (4,5,6)	3	0.862
=22	Hoddle, Glenn	Swindon (1); Chelsea (2,3,4)	4	0.862

Table 7.6 - *Continued*

Rank	Manager	Clubs (seasons observed)	Number of Observations	Mean Efficiency
25	Reid, Peter	Manchester City (1); Sunderland (4,5,6)	4	0.860
26	Robson, Bryan	Middlesbrough (3,4,5,6)	4	0.859
=27	Pulis, Anthony	Bournemouth (1,2); Gillingham (4,5,6)	5	0.857
=27	Wignall, Steve	Colchester (3,4,5,6)	4	0.857
=27	Ternent, Stan	Bury (4,5,6)	3	0.857
30	Wilkins, Ray	QPR (3,4); Fulham (6)	3	0.854
Selected Others				
32	Dalglish, Kenny	Blackburn (1,2,3); Newcastle (5,6)	5	0.850
45	Taylor, Graham	Wolves (2,3,4,); Watford (6)	4	0.828
46	Kinnear, Joe	Wimbledon (1,2,3,4,5,6)	6	0.826
62	Graham, George	Arsenal (1,2,3); Leeds (5,6)	5	0.806
66	Smith, Jim	Portsmouth (1,2,3); Derby (4,5,6)	6	0.801
72	Evans, Roy	Liverpool (2,3,4,5,6)	5	0.792
79	Wilkinson, Howard	Leeds (1,2,3,4)	4	0.778
94	Walker, Mike	Norwich (1,2); Everton (2,3); Norwich (5,6)	6	0.731
105	Atkinson, Ron	Aston Villa (1,2,3); Coventry (3,4,5); Sheffield Wed (6)	7	0.669
108	Harford, Ray	Blackburn (4,5); West Bromwich Albion (5,6); QPR (6)	5	0.562[d]

Notes: Efficiency scores based on MODEL 4. Total N = 108. For seasons observed: 1 = 1992/93, 2 = 1993/94 , 3 = 1994/95, 4 = 1995/96, 5 = 1996/97, 6 = 1997/98.
[a] To qualify a manager must have been observed on at least three occasions (full or part seasons).
[b] Joint manager with Mick Gooding until season 1997/98.
[c] Joint manager with Steve Gritt until season 1995/96.
[d] Excluding the ten games in charge of Blackburn at the start of the 1996/97 season increases Ray Harford's mean efficiency to 0.678. (In the ten games Ray Harford was in charge before termination no wins were recorded. Not surprisingly, his efficiency score for that season was less than 10 per cent).

The differences between the most and least efficient managers can be explained in terms of the same characteristics that were believed to be important in the inefficiency effects models[41]. As before, the most important human capital characteristics are the number of months managing current club (MMCC) and number of international caps (CAPS). Even though some of the least efficient managers have undoubted managerial experience, they tend to have limited experience with the current club and almost all lack quality in terms of their playing characteristics (i.e., none gained international caps). Club factors are important too, especially in relation to prior affiliation.

An alternative method for considering managerial worth is to analyse the relationship between managerial change and team performance. Closer examination of Table 7.6 suggests a negative correlation between managerial efficiency and number of teams managed (see also Figures 7.1 (a) – 7.1 (d)). The correlation coefficient is negative but not strong (-0.442). Only one manager in the top 10 managed more than one club, and only two managers in the top 30 managed more than two (Martin O'Neill and Steve Thompson). A slightly stronger correlation (-0.504) exists between club efficiency and the number of managers (see Table 7.7). The six clubs persevering with the same manager achieved, on average, a 3 per cent higher efficiency than those clubs who changed the manager once, a 8 per cent higher efficiency than clubs who changed between two and three times, and over 12 per cent higher efficiency than clubs who changed the manager more than three times.

[41] Details from the author on request.

Table 7.7 Mean Efficiency by Team

Rank	Club Name	Number of Observations[a]	Number of Managers	Mean Efficiency
1	Crewe Alexandra	6	1	0.921
2	Walsall	5	2	0.907
3	Macclesfield Town	1	1	0.903
4	Wrexham	6	1	0.899
5	Tranmere Rovers	6	2	0.897
6	Reading	7	3	0.886
7	Charlton Athletic	6	1	0.879
8	Wycombe Wanderers	6	4	0.875
9	Stockport County	6	3	0.875
10	Port Vale United	6	1	0.871
11	Manchester United	6	1	0.870
12	Newcastle United	7	2	0.870
13	Colchester United	7	3	0.865
14	Chelsea	8	5	0.864
15	Bury Town	6	2	0.860
16	Chesterfield	7	2	0.858
17	Blackpool	6	4	0.858
18	Barnsley	6	3	0.855
19	York City	7	2	0.853
20	Arsenal	6	3	0.852
21	Gillingham	7	4	0.850
22	Bradford City	8	4	0.844
23	Carlisle United	7	4	0.841
24	West Ham United	6	2	0.839
25	Shrewsbury Town	6	3	0.829
26	Middlesbrough	6	2	0.829
27	Rochdale United	7	3	0.827
28	Wimbledon	6	1	0.826
29	Oxford United	7	3	0.822
30	Birmingham City	7	3	0.821
31	Ipswich Town	7	3	0.821
32	Portsmouth	8	3	0.820
33	Liverpool	7	2	0.820
34	Millwall	8	4	0.820
35	Huddersfield Town	6	4	0.818
36	Preston North End	8	3	0.818
37	Scunthorpe United	9	5	0.816
38	AFC Bournemouth	6	2	0.816
39	Sunderland	8	4	0.815

Table 7.7 - *Continued*

Rank	Club Name	Number of Observations[a]	Number of Managers	Mean Efficiency
40	Wolverhampton Wanderers	8	3	0.815
41	Bristol City	8	3	0.810
42	Derby County	6	3	0.808
43	Tottenham Hotspur	8	4	0.806
44	Lincoln City	6	4	0.805
45	Hereford United	5	3	0.805
46	Leicester City	8	3	0.804
47	Stoke City	8	4	0.799
48	Southend	8	6	0.798
49	Wigan Athletic	8	5	0.797
50	Barnet	8	6	0.795
51	Cambridge United	8	5	0.795
52	Swansea	8	3	0.792
53	Darlington	8	4	0.790
54	Fulham	7	4	0.790
55	Rotherham United	6	4	0.787
56	Grimsby Town	8	4	0.784
57	Leeds United	6	2	0.783
58	Brentford	7	3	0.782
59	Aston Villa	8	3	0.782
60	Hartlepool United	9	6	0.780
61	Doncaster Rovers	7	5	0.778
62	Burnley	7	3	0.775
63	Watford	6	4	0.771
64	Bolton Wanderers	7	3	0.770
65	Northampton Town	7	3	0.769
66	Mansfield Town	6	3	0.769
67	Torquay United	8	4	0.768
68	Leyton Orient	7	4	0.766
69	Crystal Palace	8	4	0.766
70	Bristol Rovers	7	3	0.765
71	Southampton	7	5	0.764
72	Luton Town	7	3	0.763
73	Peterborough United	8	5	0.763
74	Queens Park Rangers	8	4	0.760
75	Oldham Athletic	8	3	0.759
76	Sheffield United	7	3	0.758
77	Exeter City	7	3	0.757
78	Coventry	9	4	0.756

Table 7.7 - *Continued*

Rank	Club Name	Number of Observations[a]	Number of Managers	Mean Efficiency
79	Sheffield Wednesday	7	3	0.754
80	Hull City	6	2	0.747
81	Swindon Town	7	3	0.745
82	Scarborough Town	8	5	0.743
83	Cardiff City	10	5	0.732
84	Blackburn Rovers	6	3	0.728
85	Everton	8	4	0.725
86	Notts County	9	6	0.724
87	Norwich City	8	5	0.719
88	West Bromwich Albion	9	5	0.702
89	Manchester City	7	5	0.697
90	Brighton	10	5	0.695
91	Halifax Town	2	2	0.693
92	Chester City	8	5	0.681
93	Plymouth Argyle	7	4	0.667
94	Nottingham Forest	7	3	0.625

Note: Efficiency scores based on MODEL 4.
[a] A separate observation is recorded in every season and where any mid-season change takes place.

Managerial turnover often follows a run of poor results (Fizel and D'itri, 1997; Audas *et al.* 2000)[42]. The concern here is the effect of a change of manager on subsequent team performance (just as earlier we looked at a change of club on managerial performance). Clubs which change the manager face a trade-off between providing a better job match (i.e. replacing a "poor" manager) and the disruptive effect that can arise from changing the manager[43]. Grusky (1963), who first considered the question of club performance following the replacement of the manager, observed that the disruptive effect in American baseball results in further deterioration in team performance.

[42] This line of reasoning assumes all managerial termination is involuntary (i.e., when the club instigates termination). Voluntary terminations (i.e., when the manager instigates termination) do occur but less frequently than involuntary terminations (Audas *et al.* 2000).

More generally, other studies in basketball (Eitzen and Yetman, 1972) and American football (Brown, 1982) have found that replacing the manager has little effect on team performance. There are two contrasting reasons for this. Firstly, the negative disruptive effect is cancelled out by the positive improvement in the job match (Pfeffer and Davis-Blake, 1986). Alternatively, the characteristics of the incoming manager are similar to those of the outgoing manager. Practitioners here argue that the closer are the characteristics of the incoming manager to the outgoing manager, the less likely it is that there will be succession effects. A positive succession effect will only occur if the abilities of the incoming manager are greater than that the abilities of the outgoing manager.

To test whether managerial efficiency is influenced by managerial turnover we compare the efficiency of the incoming manager with the efficiency of the outgoing manager in the season when the change occurred[44]. Of the 661 observations in this study 139 involve managers whose contracts were terminated mid-season. There were a total of 143 mid-season starts, nine of which were terminated before the season came to a close and a further 15 were terminated during the close season.

The mean efficiency of managers who are employed by the same club throughout the duration of the season is 0.832 (see also Figure 7.1 (a)). The average efficiency of all terminated managers is 0.716 and the average efficiency of all managers who started mid-season is 0.790. The differences between these means are statistically significant at the 1 per cent level. These findings suggest that whilst mid-season managerial changes

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[43] There is a paradox here. On the one hand, managers seem to be motivated by the threat of dismissal. On the other hand, when clubs change the manager there is usually a disruptive effect.
[44] Most other studies have tended to compare average performance over the complete spell. However, in many cases, due to limited number of seasons sampled, we seldom have complete tenure lengths for

do lead to improve performance, clubs will, on average, incur an 8 per cent reduction in performance when compared with those clubs where the same manager remains throughout the season (equivalent to foregoing two wins). These findings are consistent with those of Scully (1995) in North American sports. However, we can only speculate on the level of efficiency that the outgoing manager may have achieved had he stayed until the end of the season[45]. Perhaps the safest conclusion we can offer here is that manager change should occur during the close season. If mid-season succession is absolutely necessary the club should ensure that the incoming manager has better (efficiency improving) attributes than the outgoing manager.

7.6 Summary

This chapter has investigated the sources of managerial efficiency in English football over the period 1992-1998. Specifically, we have examined the impact of the manager's playing career and managerial career to date (human capital factors) and club-specific factors (incentive factors) on efficiency. Although this is a study of the football industry many of the observed effects are consistent with economic theory. Thus the football industry is far from atypical. Considered in the context of previous studies – in sport and other industrial sectors - we find support for both the human capital and incentive-based interpretations of performance. The main findings are that club-specific factors as well as human capital factors have a significant effect on the efficiency of managers and the coefficients of the human capital variables are unaltered when the club-specific factors are included.

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many managers. Comparing the win ratio of the incoming and outgoing manager will lead to similar conclusions.

So what can we say about what really makes a good manager? At a general level, managerial experience is found to be more important than prior playing experience, and specific managerial experience (job tenure) is more important than general managerial experience (managerial longevity). Overall, the quality of experience gained by the individual (such as number of international appearances) is more important than the quantity (such as total number of league games played) and learning is enhanced if the manager has some kind of prior affiliation with the club. The efficiency of managers is also affected by the size of the club, average tenure levels and the wages paid. Unfortunately, data limitations prevent us investigating in detail how wage incentives determine managerial efficiency.

In generating individual efficiency scores our analysis has served a second purpose: to test whether the manager matters. To estimate the impact of the manager we compare the actual managerial efficiency with best-practice efficiency and observe the effect it might have on team output. Employing the right manager can potentially improve team performance by about 20 per cent. We also conducted a preliminary analysis of succession effects to see whether changing the manager during the season makes a difference. Generally speaking mid-season managerial changes do lead to improved performance, but clubs incur an 8 per cent reduction in efficiency compared with clubs which have the same manager in post throughout the season. This is equivalent to foregoing two wins, which in many instances can make the difference between survival or relegation. However we must stress that because winning is a zero sum game not all managers can be equally successful.

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[45] It is interesting to note that the correlation between the number of games in charge in any one season and efficiency is only 0.343.

Finally, and of most concern, it is clear that managerial efficiency is declining over time. The increasing pressure for success in football is leading to high levels of managerial turnover. In order to arrest the trend of high turnover leading to lower efficiency, decision-makers (chairpersons, directors and club shareholders) need to consider carefully whom they appoint as manager, and the frequency with which they change the manager, if they are interested in seeing the club perform optimally.

CHAPTER 8

CONCLUSIONS

Using stochastic frontier analysis this thesis has provided estimates of technical efficiency for a panel of managers in the English football industry over the period 1992 to 1998. The thesis has also analysed the variation in efficiency across managers in terms of manager human capital and incentive (agency) effects. This is the first study to directly link managerial efficiency to the characteristics of individual managers for any industry in the UK and the first study anywhere to use incentive based factors as determinants of managerial efficiency. Although some may question whether patterns of behaviour pertaining to professional football managers are easily generalisable elsewhere, I would argue that football is of sufficient cultural, social and (increasingly) economic importance to justify study in its own right.

This thesis has contributed to the existing literature in two ways. Firstly, central to the success of any econometric model is the appropriateness of the specification and estimation procedure. Such considerations take on an added significance in stochastic frontier models because the efficiency scores are estimated as deviations from the production frontier (the efficiency scores are contained in the residuals). With this in mind, we follow other studies in obtaining efficiency scores using competing estimation procedures (incorporating both time-invariant and time-varying efficiency). Unlike previous work, however, we also examine the sensitivity of the efficiency scores to alternative input and output measures. In common with the findings of other studies (in agriculture and the aviation industry) we find that the efficiency scores provided by competing estimation methods vary substantially. The efficiency rankings though are reasonably similar. But there is much less association between the efficiency scores provided by the alternative input and output measures, even though the measures themselves are highly correlated. This is an important finding because it suggests that the choice of input and output measures is just as important as the choice of estimation procedure. From an analytical viewpoint, therefore, it is recommended that researchers using frontier analysis should consider not only the choice of estimation procedure, but also the choice of production parameters (where possible).

Secondly, the overriding aim of many studies of the managerial labour market has been to focus on incentives or human capital factors as determinants of managerial pay. Few studies have examined whether incentives or human capital actually improve managerial performance. We bridge this gap by analysing possible human capital *and* incentive factors as determinants of efficiency. We find that the variation in efficiency across managers lends support to the human capital interpretation of performance. In particular, the results show that current job tenure and the quality of previous playing experience are most important. Having some kind of prior affiliation with the club also has a positive impact on efficiency. In contrast, quantity of playing experience and the level of general managerial experience are largely unimportant. There is also clear evidence to suggest that incentives also affect efficiency. Specifically, wage levels and club size both have a positive effect on efficiency, whereas average tenure length is negatively related to efficiency. This latter finding suggests that the threat of dismissal does act as an effective incentive. The clear message here is that managerial performance is affected by both the characteristics of the manager and the environment in which the manager works. Therefore, a further recommendation is that researchers should consider both human capital and incentive factors as performance determinants.

In general the most efficient managers do not manage the most successful teams. The best managers are those that can keep a team in a division or gain promotion when the quality of the playing resources compared to other teams would suggest otherwise. Critically the manager does seem to make a difference to team performance. The model predicts that approximately two-thirds of the variation in team performance is attributable to the quality of the playing resources and about one-third is attributable to the manager. The impact of purely random factors is minimal. There is also considerable variation in the efficiency of individual managers. Mean efficiency is estimated to be around 75 to 80 per cent, implying a potential improvement in team performance of about 20 – 25 per cent through an improvement in the manager's efficiency. However, not all managers can be successful because winning is a zero sum game. Nevertheless, it is also true that even a small change in managerial efficiency can often make the difference between, for example, survival and relegation.

There is strong evidence to suggest that the overall level of efficiency is falling. The main reason for this appears to be the increasing pressure on managers to be successful which is leading to higher and higher levels of managerial turnover. Much of this stems from an over-reliance by club owners of evaluating the manager purely on the basis of results. We presented some preliminary findings on the impact of managerial succession on team performance. Significantly, it was found that clubs face an apparent paradox. On the one hand, managers seem to be motivated by the threat of dismissal, but on the other hand, managerial turnover is often disruptive to team performance.

Some experimentation was needed and a number of restrictive assumptions were required in order to derive the measure of team quality used to estimate the production frontier. Even so, the predicted player valuation measure is both theoretically and empirically appealing (more so than the wages measure). However, the amount of data required to construct this variable has restricted the number of seasons we have been able to sample. This not only precludes a more detailed account of the career observations of managers, but it also means we have been unable to compare present day managers with some of the most "successful" managers in other time-periods (e.g., Don Revie, Bill Shankly, Brian Clough and Bob Paisley).

Access to a data set covering the most recent time-periods would also allow us to compare the player valuation measure with the actual performance data that is now becoming available. Also, we have only presented results pertaining to three incentive effects. In particular, the study would benefit from more detailed information regarding the wages paid to individual managers. This would enable us, for example, to compare and contrast experience-efficiency profiles with wage-efficiency profiles. The nature of the study has also limited our ability to add to the ongoing debate as to how qualifications gained through education and formal training influence efficiency.

Not withstanding these limitations, this thesis has identified some of the key characteristics that determine managerial efficiency. These results offer a valuable insight into what makes a good (i.e., efficient) manager as opposed to what makes a successful manager and should assist policy-makers when making the often-crucial decision of appointing a manager. The results also suggest that the qualities that make a good football manager are not too dissimilar to the qualities required of managers in other industrial sectors.

In the future it would be useful to extend the work in a number of areas. Firstly, this research is based on one dimension of managerial performance: maximising team performance from a given set of playing resources. This relates to a measure of technical efficiency. One aspect that has been neglected is the relative performance of the manager in the transfer market. It would be interesting to measure how good the manager is at finding "bargain" players who demand a high resale value and how much transfer expenditure is available to him. This would allow us to derive an estimate of a manager's allocative efficiency (cost minimisation or profit maximisation) and, in conjunction with technical efficiency, the two could be used to determine an overall measure of managerial (economic) efficiency.

Secondly, the scope of the study could be widened to encapsulate other production frontier techniques. It would be useful to compare stochastic frontier estimation with deterministic frontier or non-parametric techniques such as data envelopment analysis as well as other time-varying models. Possible use of non-nested test procedures and Monte Carlo analysis would also prove useful in evaluating further the appropriateness of the competing estimation procedures, particularly for time-varying models.

Finally, this thesis has identified some of the factors that are important in modelling football production and determining efficiency. As noted above, it would be useful to see how robust these efficiency results are to other team performance measures and whether other human capital and agency factors could be included. With improvements in the availability of data the framework applied here could be used to compare the performance of managers in the corporate sector to test whether the qualities required of corporate managers are indeed similar to those of football managers.

APPENDIX I

PREDICTING INDIVIDUAL PLAYER VALUATIONS: HOW ACCURATE IS THE SOCCER TRANSFERS MODEL?

The purpose of this appendix is to consider how well the predicted player valuations perform in practice. We consider two approaches to this. The first involves comparing predicted valuations with actual valuations (transfer fees). The second considers the performance of the predicted valuation as a productivity measure.

Table A1.1 compares the 46 permanent transfers that involved a fee during July 1996 with the predicted valuations (fees). The total expenditure on fees was almost £41 million compared to a predicted total of just under £35 million. The transfer of Alan Shearer (Blackburn Rovers to Newcastle United) accounts for much of the difference: actual transfer value of £15 million versus a predicted value of £7.6 million. In addition, there are a number of other large outliers (both positive and negative). For example, Kingsley Black's actual transfer fee was 16 times lower than his predicted value, whereas the fees secured for Martin O'Connor and Paul Furlong were several times higher than expected. On the other hand, in a number of cases the predicted value is close to the actual fee. This is particularly true of the lower end of the market. Overall, the average actual transfer fee is £132,449 greater than the predicted value.

Table A1.1 A Comparison of Permanent Transfers Involving a Fee with Predicted Transfer Valuations (July 1996[a])

Player	Actual Fee (£)[b]	Predicted Fee (£)[c]	Difference[d]
Allen, Chris	450,000	2,440,253	-1,990,253
Booth, Andy	2,700,000	4,473,073	-1,773,073
Martyn, Nigel	2,250,000	2,965,732	-715,732
Black, Kingsley	25,000	406,606	-381,606
Payton, Andy	350,000	689,752	-339,752
Izzet, Muzzy	650,000	968,892	-318,892
Widderington, Tommy	300,000	611,804	-311,804
Jemson, Nigel	60,000	341,732	-281,732
O'Connell, Brendan	125,000	317,195	-192,195
Appleby, Matty	200,000	281,475	-81,475
Wrack, Darren	100,000	177,287	-77,287
Forsyth, Richard	200,000	269,737	-69,737
Houghton, Scott	60,000	127,348	-67,348
Jepson, Ronnie	40,000	79,685	-39,685
Beaumont, Chris	30,000	66,829	-36,829
Matthew, Damian	65,000	99,561	-34,561
Purse, Darren	100,000	133,787	-33,787
Tolson, Neil	60,000	81,318	-21,318
Peschisolido, Paul	600,000	616,735	-16,735
Austin, Kevin	30,000	46,526	-16,526
Watson, Paul	13,000	23,846	-10,846
McCarthy, Paul	100,000	110,478	-10,478
Freeman, Darren	15,000	22,134	-7,134
Wilkins, Richard	30,000	30,779	-779
Butler, Paul	100,000	96,774	3,226
Carey, Brian	100,000	91,587	8,413
Baird, Ian	35,000	23,983	11,017
Hunter, Barry	400,000	386,820	13,180
Peake, Jason	80,000	60,104	19,896
Ablett, Gary	390,000	364,377	25,623
Jones, Paul	60,000	33,883	26,117
Horne, Barry	250,000	203,103	46,897
Roberts, Iwan	1,000,000	952,753	47,247
Jones, Gary	150,000	102,730	47,270
Sandford, Lee	500,000	445,514	54,486
Slade, Steve	350,000	235,562	114,438
Brabin, Gary	200,000	82,013	117,987
Groves, Paul	600,000	421,167	178,833
O'Connor, Martin	350,000	100,766	249,234
Newell, Mike	775,000	387,003	387,997
Speed, Gary	3,500,000	2,964,383	535,617
Stewart, Marcus	1,200,000	641,318	558,682
Bowyer, Lee	2,800,000	2,169,108	630,892
Furlong, Paul	1,500,000	572,182	927,818
McAllister, Gary	3,000,000	1,424,686	1,575,314
Shearer, Alan	15,000,000	7,657,951	7,342,049
TOTALS	40,893,000	34,800,331	6,092,669

[a] July 1996 transfers were chosen because the predicted values are based on August 1996 prices.
[b] Rothmans Football Yearbook (1997).
[c] SOCCER TRANSFERS (VALUE 6).
[d] Actual fee minus predicted fee.

There are two main factors that are likely to account for these differences. First of all, the tendency for the fee to be higher than expected can be explained by the competitive nature of the bidding process especially for the highly valued players. Conversely, lower actual fees compared to the predicted value results from an absence of competition for the player or when the selling club needs a quick sale because of impending financial difficulties. Secondly, the direction in which the player moves will also have an impact. Recall that the predicted valuation assumes a mid-division selling club and a mid-division buying club. If a player moves up (down) a division(s) the actual fee paid is likely to be more (less) than that predicted.

The effect on the predicted value when a player is transferred to another club is demonstrated in Table A1.2. The valuations of the 16 players that meet the appearance criteria in Manchester United's championship winning side in the inaugural Premier League season (1992/93) are tracked over the six seasons of the study. At the end of the 1997/98 season only five of the original 16 players remained with Manchester United. Some players had retired, others had moved (or were about to move) into management. The majority of the players were transferred to another club. For example, Steve Bruce's value dropped significantly when he was transferred to Birmingham City (Division 1), as did the value of Darren Ferguson when he moved to Wolverhampton Wanderers (also of Division 1). As expected, movement within the same division has a smaller impact; the valuation of Mark Hughes has declined steadily over the six seasons whereas the value of Andrei Kanchelskis actually increased after he joined Everton (Premier League).

Table A1.2 Manchester United's Championship Winning Side 1993: Predicted Player Valuations over Time

Player	Pos.	Value (£)[a]					
		1992	1993	1994	1995	1996	1997
Schmeichel, Peter	GK	2,090,215	2,102,380	1,845,891	2,062,977	1,882,361	1,519,521
Irwin, Denis	DF	2,720,492	2,570,404	2,164,829	1,761,540	1,337,789	1,036,926
Pallister, Gary	DF	2,497,325	2,356,620	2,029,171	1,710,553	1,189,719	1,012,829
Bruce, Steve	DF	969,367	737,144	505,621	329,344	76,221[b]	33,907
Parker, Paul	DF	1,736,070	1,728,102	N/A[c]	N/A[c]	N/A[c]	N/A[d]
Phelan, Mike	DF	946,229	N/A[c]	164,556[e]	N/A[c]	N/A[c]	N/A[c]
McClair, Brian	MD	4,477,141	3,271,080	1,438,035	1,297,912	681,312	638,041
Ince, Paul	MD	2,166,839	3,190,751	3,153,986	N/A[f]	N/A	2,005,795[g]
Robson, Bryan	MD	425,602	164,503	38,958[h]	N/A[I]	N/A	N/A
Ferguson, Darren	MD	1,160,594	619,451[j]	462,848	574,611	399,900	446,056
Blackmore, Clayton	MD	1,762,751	N/A[c]	233,608[h]	N/A[c]	2,433,825[k]	N/A[c]
Giggs, Ryan	FW	2,829,128	4,285,669	4,925,298	4,693,170	5,865,485	5,383,973
Cantona, Eric	FW	2,302,708	3,012,524	3,041,207	3,241,207	2,911,505	N/A[d]
Sharpe, Lee	FW	2,425,714	3,897,339	4,552,346	2,243,589	1,965,262[l]	N/A[c]
Kanchelskis, Andrei	FW	1,961,460	1,490,903	2,155,932	3,111,307[m]	3,686,807	N/A[f]
Hughes, Mark	FW	3,412,185	3,152,282	2,417,877	1,775,813[n]	1,405,502	1,055,862

Notes: GK = goalkeeper; DF = defender; MD = midfielder; FW = forward. N/A = not available.
[a] VALUE 6 (constant (Aug. 1996) prices).
[b] Transferred to Birmingham.
[c] Did not fulfil appearance criteria.
[d] Retired from playing.
[e] Transferred to West Bromwich Albion.
[f] Transferred overseas.
[g] Transferred to Liverpool.
[h] Transferred to Middlesbrough.
[i] Moved into management (Middlesbrough).
[j] Transferred to Wolverhampton Wanderers.
[k] Middlesbrough promoted into Premier League.
[l] Transferred to Leeds.
[m] Transferred to Everton.
[n] Transferred to Chelsea.

More evidence on the differences in predicted valuations between divisions is provided in Table A1.3. The average Premier League player is valued between four and five times higher than a Division 1 player who in turn is valued four to five times higher than the average Division 2 player. The average Division 3 player can expect to be worth about half that of a Division 2 player. And the equivalent of 43 Division 3 players can be purchased for one Premier League player. Although the process used to generate the valuations is influenced by the assumptions introduced about the selling club and the buying club they are indicative of the way transfer fees are determined in practice.

Table A1.3 Predicted Player Valuations by Division ("Average" Player)

Season	Premier League	Football League		
		Division 1	Division 2	Division 3
1992/93	1,831,811	451,663	87,944	42,102
1993/94	1,794,882	452,003	86,695	43,744
1994/95	1,835,282	428,299	88,257	43,217
1995/96	1,991,935	437,018	95,811	40,033
1996/97	2,001,358	420,472	91,375	39,866
1997/98	2,047,679	438,113	99,952	42,845

Note: VALUE 2 (constant (August 1996) prices).

Another notable feature of the data concerns the predicted valuations by position. Forward players are the most valuable, followed by midfield players and defenders. Generally, this is what we would expect. Teams cannot win matches if they do not score goals. On the other hand, teams cannot win if they concede as many goals as they score. This is followed up in Table A1.4 where we analyse the predicted valuation for the average player by position in the Premier League for the six seasons of the study. The average forward player is consistently valued between £0.6 million and £0.8 million higher than the average midfield player; the differences between the other positional categories are much smaller and the valuations, even after being deflated to August 1996 prices, have tended to increase for all playing positions. This latter finding seems to be a reflection of the quality of the players playing in the Premier League (since 1992 there has been a massive influx of foreign internationals), and an increasing emphasis on "attacking" football in particular. In contrast, the valuation for the average player in the other divisions (Table A1.3) has remained reasonably constant.

Table A1.4 Predicted Valuations for Premier League Players by Positions ("Average" Player)

Season	Playing Position			
	GK	DF	MD	FW
1992/93	1,762,943	1,642,761	1,703,020	2,269,967
1993/94	1,630,066	1,516,099	1,693,054	2,317,036
1994/95	1,529,618	1,552,411	1,621,017	2,385,081
1995/96	1,612,040	1,640,666	1,721,061	2,736,206
1996/97	1,480,288	1,594,647	1,850,966	2,653,884
1997/98	1,532,797	1,734,352	1,932,823	2,734,236

Notes: VALUE 6 (constant (August 1996) prices).
GK = goalkeeper; DF= defender; MD = midfielder; FW = forward.

The dominance of forward players is also illustrated in Table A1.5, which reports the top 50 player values. Of the top 50 places (from a total of 9,786 values generated) 39 (and 29 of the top 30) are occupied by forward players, three places are occupied by midfield players and only one place is occupied by a defender. This seems to reflect the higher probability of a forward player being transferred and the importance placed on the ability to score goals (see also Carmichael *et al.* 1999 for an illustration of this in relation to actual transfer fees). Interestingly, even though goalkeepers are generally valued the least, they occupy seven places in the top 50. There is also evidence for the higher values to be grouped in the later seasons; 33 of the values occur for the seasons 1994/95 to 1996/97. Finally, only four players occupy the top 10 positions, while one player - Alan Shearer - occupies five of these positions.

Table A1.5 Top Fifty Valuations 1992/93 to 1997/98[a]

Rank	Player	Position	Season	Value (£)
1	Cole, Andy	FW	1995/96	10,788,889
2	Fowler, Robbie	FW	1996/97	10,496,403
3	Fowler, Robbie	FW	1997/98	10,279,494
4	Cole, Andy	FW	1994/95	9,502,672
5	Shearer, Alan	FW	1994/95	8,654,470
6	Shearer, Alan	FW	1996/97	7,657,951
7	Shearer, Alan	FW	1995/96	7,389,382
8	Moldovan, Viorel	FW	1997/98	7,009,960
9	Shearer, Alan	FW	1993/94	6,930,739
10	Shearer, Alan	FW	1997/98	6,848,542
11	Andersson, Andreas	FW	1997/98	6,804,883
12	Solskjaer, Ole Gunner	FW	1996/97	6,469,968
13	Fowler, Robbie	FW	1995/96	6,295,968
14	Cole, Andy	FW	1996/97	6,108,700
15	Collymore, Stan	FW	1995/96	6,016,235
16	Milosevic, Savo	FW	1995/96	5,997,857
17	Le Tissier, Matthew	FW	1994/95	5,941,159
18	Giggs, Ryan	FW	1996/97	5,865,485
19	Booth, Andy	FW	1997/98	5,856,097
20	Milosevic, Savo	FW	1997/98	5,850,632
21	Shearer, Alan	FW	1992/93	5,724,915
22	Hartson, John	FW	1997/98	5,698,205
23	Sutton, Chris	FW	1994/95	5,683,976
24	Barmby, Nick	FW	1997/98	5,647,553
25	Sutton, Chris	FW	1995/96	5,629,062
26	Seaman , David	GK	1992/93	5,554,786
27	Barmby, Nick	FW	1996/97	5,534,320
28	Hirst, David	FW	1992/93	5,489,040
29	Flo, Tor Andre	FW	1997/98	5,448,797
30	Giggs, Ryan	FW	1997/98	5,383,973
31	Speed, Gary	MD	1993/94	5,381,658
32	Ferguson, Duncan	FW	1995/96	5,381,038
33	Wallace, Rod	FW	1992/93	5,365,030
34	Le Tissier, Matthew	FW	1995/96	5,341,462
35	James, David	GK	1997/98	5,306,272
36	Collymore, Stan	FW	1996/97	5,296,822
37	James, David	GK	1995/96	5,266,484
38	Cole, Andy	FW	1997/98	5,259,810
39	Martyn, Nigel	GK	1992/93	5,167,060
40	McManaman, Steve	FW	1995/96	5,164,921
41	Deane, Brian	FW	1993/94	5,160,371
42	Speed, Gary	MD	1992/93	5,147,539
43	Barmby, Nick	FW	1995/96	5,147,052
44	James, David	GK	1996/97	5,136,685
45	Beckham, David	MD	1997/98	5,128,032
46	Dailly, Christian	DF	1997/98	5,091,993
47	Deane, Brian	FW	1992/93	4,988,693
48	Gunn, Bryan	GK	1994/95	4,962,010
49	Wallace, Rod	FW	1993/94	4,947,111
50	Gunn, Bryan	GK	1993/94	4,930,513

Notes: Positions based on classification given in Rothmans Football Yearbook (various editions). VALUE 6 (constant (August 1996) prices).
[a] Valuations predicted for the start of season under observation (e.g., 1995/96 season refers to a predicted value as at August 1995).

Perhaps the strongest piece of evidence in favour of using the predicted valuation approach is the way the predicted value relates to player age. The majority of the Manchester United team which won the Premier League in 1993 were considered to be at the peak of their game (football players usually reach their peak between the ages of 27 – 29). Returning to Table A1.2 we find that consistent performers (in terms of appearances made and goals scored) such as Denis Irwin and Gary Pallister saw their predicted valuations fall from £2.7 million and £2.5 million in 1992 to just over £1 million in 1997. The valuation of midfielder Brian McClair fell equally dramatically and while the valuation of forward players is slightly more unpredictable, there is still a general decline in value once a critical age is reached. A further example of this trend is provided in Table A1.5 where Alan Shearer's value in 1997 value is nearly £2 million lower than his 1994[1].

The relationship between player age and predicted valuation for all Premier League players who played in the 1997/98 season is shown in Figure A1.1 and resembles the age-productivity profile commonly observed in the human capital literature. In Figure A1.1 no player above the age of 29 has a valuation above £4 million, and no player over the age of 32 has a valuation greater than £2 million. At the opposite end, players in the early part of their career (e.g., aged 22 and below) can expect a valuation below £3 million. On this basis, the predicted valuation method seems to be an adequate measure of a player's unobserved productivity.

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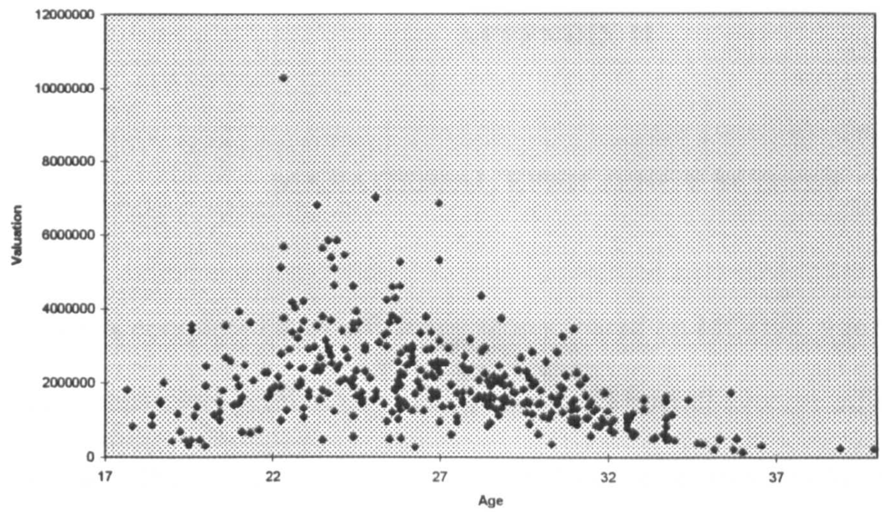
[1] The approach taken in this study is to generate a value for each player in each season (i.e., six different values for a player who played in each of the six seasons sampled provided he meets the appearance criteria). One criticism of this approach is that it does not take account of a player's inherent ability. The fact that a player eventually wins international caps at the age of 24 is an indicator of inherent ability, and should therefore influence the value attributed to him for the season when he was aged 18. The decision was made to construct values for each player each season because complete careers of the players was not available in the majority of cases. There is also a counter argument that suggests a player's potential is, in some way, enhanced by the quality of the managerial and coaching resources. Furthermore, a player's

Figure A1.1 Age-Predicted Value Profile for Premier League Players (1997/98)[a]



[a] VALUE 6.

Overall the predicted valuation model seems to provide an adequate representation of the process generating actual fees. The margin of error, though large in some cases, is acceptable bearing in mind the restrictive assumptions we have had to introduce. Furthermore, the predicted value is a good approximation of player productivity.

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performance is likely to fluctuate over time due to injury, suspension and the impact that large guaranteed contracts might have on future performance.

APPENDIX II

MANAGERIAL EFFICIENCY SCORES

Below is a complete list of efficiency scores (based on MODEL 4 in Chapter 7) for each manager observed in this study. Each manager's overall average efficiency is also reported. Managers are ranked in alphabetical order by time period (season).

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Adams, Micky	4	Fulham	4	0.883	
	5	Fulham	4	0.925	
	6	Brentford	3	0.721	*0.843*
Aldridge, John	5	Tranmere Rovers	2	0.898	
	6	Tranmere Rovers	2	0.865	*0.881*
Alexander, Keith	2	Lincoln City	4	0.676	*0.676*
Allardyce, Sam	3	Blackpool	3	0.817	
	4	Blackpool	3	0.883	
	5	Notts County	3	0.402	
	6	Notts County	4	0.829	*0.733*
Anderson, Viv	2	Barnsley	2	0.846	*0.846*
Ardiles, Ossie	1	West Bromwich Albion	3	0.916	
	2	Tottenham Hotspurs	1	0.773	
	3	Tottenham Hotspurs	1	0.901	*0.863*
Atkins, Ian	1	Cambridge United	2	0.805	
	2	Doncaster Rovers	4	0.842	
	3	Northampton Town	4	0.854	
	4	Northampton Town	4	0.864	
	5	Northampton Town	4	0.827	
	6	Northampton Town	3	0.883	*0.846*
Atkinson, Ron	1	Aston Villa	1	0.894	
	2	Aston Villa	1	0.815	
	3	Aston Villa	1	0.488	
	3	Coventry City	1	0.873	
	4	Coventry City	1	0.653	
	5	Coventry City	1	0.239	
	6	Sheffield Wednesday	1	0.719	*0.669*
Ayre, Billy	1	Blackpool	3	0.882	
	2	Blackpool	3	0.869	
	3	Scarborough	4	0.380	*0.710*
Ball, Alan	1	Exeter City	3	0.796	
	2	Exeter City	3	0.782	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Ball, Alan (cont.)	2	Southampton	1	0.891	
	3	Southampton	1	0.764	
	4	Manchester City	1	0.729	
	6	Portsmouth	2	0.872	*0.806*
Barnwell, John	2	Northampton Town	4	0.663	
	3	Northampton Town	4	0.429	*0.546*
Barrow, Graham	1	Chester City	3	0.682	
	2	Chester City	4	0.894	
	3	Wigan Athletic	4	0.866	
	4	Wigan Athletic	4	0.784	
	5	Rochdale United	4	0.782	
	6	Rochdale United	4	0.846	*0.809*
Bassett, Dave	1	Sheffield United	1	0.855	
	2	Sheffield United	1	0.729	
	3	Sheffield United	2	0.712	
	4	Sheffield United	2	0.642	
	4	Crystal Palace	2	0.850	
	5	Crystal Palace	2	0.754	
	5	Nottingham Forest	1	0.239	
	6	Nottingham Forest	2	0.795	*0.697*
Bates, Chic	6	Stoke City	2	0.772	*0.772*
Beaglehole, Steve	1	Doncaster Rovers	4	0.756	
	2	Doncaster Rovers	4	0.903	*0.829*
Beck, John	1	Cambridge United	2	0.820	
	1	Preston North End	3	0.765	
	2	Preston North End	4	0.790	
	3	Preston North End	4	0.827	
	4	Lincoln City	4	0.775	
	5	Lincoln City	4	0.796	
	6	Lincoln City	4	0.847	*0.803*
Bergera, Danny	1	Stockport County	3	0.858	
	2	Stockport County	3	0.873	
	3	Stockport County	3	0.841	
	5	Rotherham United	3	0.649	*0.805*
Bond, John	1	Shrewsbury Town	4	0.786	*0.786*
Bonds, Billy	1	West Ham United	2	0.885	
	2	West Ham United	1	0.908	*0.897*
	6	Millwall	3	0.625	
Brady, Liam	2	Brighton and Hove Albion	3	0.918	
	3	Brighton and Hove Albion	3	0.837	
	4	Brighton and Hove Albion	3	0.715	*0.823*
Branfoot, Ian	1	Southampton	1	0.843	
	2	Southampton	1	0.680	
	3	Fulham	4	0.850	
	4	Fulham	4	0.488	*0.715*
Buckley, Alan	1	Grimsby Town	2	0.887	
	2	Grimsby Town	2	0.845	
	3	Grimsby Town	2	0.765	
	3	West Bromwich Albion	2	0.848	
	4	West Bromwich Albion	2	0.725	
	5	West Bromwich Albion	2	0.603	
	6	Grimsby Town	3	0.667	*0.763*
Bullivant, Terry	5	Barnet	4	0.885	
	6	Reading	2	0.737	*0.811*
Burkinshaw, Keith	2	West Bromwich Albion	2	0.792	
	3	West Bromwich Albion	2	0.279	*0.535*
Burley, George	3	Colchester United	4	0.917	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Burley, George (cont.)	3	Ipswich Town	1	0.761	
	4	Ipswich Town	2	0.861	
	5	Ipswich Town	2	0.919	
	6	Ipswich Town	2	0.904	***0.872***
Burrows, Frank	1	Swansea City	3	0.870	
	2	Swansea City	3	0.762	
	3	Swansea City	3	0.784	
	4	Swansea City	3	0.731	
	6	Cardiff City	4	0.591	***0.748***
Busby, Viv	1	Hartlepool United	3	0.817	
	2	Hartlepool United	3	0.850	***0.833***
Butcher, Terry	1	Sunderland	2	0.824	
	2	Sunderland	2	0.841	***0.833***
Buxton, Mick	2	Sunderland	2	0.874	
	3	Sunderland	2	0.537	
	4	Scunthorpe United	4	0.859	
	5	Scunthorpe United	4	0.825	***0.774***
Case, Jimmy	4	Brighton and Hove Albion	3	0.771	
	5	Brighton and Hove Albion	4	0.371	***0.571***
Chambers, Phil	2	Scarborough	4	0.856	***0.856***
Chard, Phil	1	Northampton Town	4	0.863	***0.863***
Chung, Sammy	3	Doncaster Rovers	4	0.856	
	4	Doncaster Rovers	4	0.786	***0.821***
Clark, Frank	2	Nottingham Forest	2	0.773	
	3	Nottingham Forest	1	0.916	
	4	Nottingham Forest	1	0.811	
	5	Nottingham Forest	1	0.175	
	5	Manchester City	2	0.737	
	6	Manchester City	2	0.458	***0.645***
Clemence, Ray	2	Barnet	3	0.759	
	3	Barnet	4	0.754	
	4	Barnet	4	0.867	***0.794***
Clough, Brian	1	Nottingham Forest	1	0.665	***0.665***
Compton, Phil	1	Torquay United	4	0.831	***0.831***
Cooper, Terry	1	Birmingham City	2	0.889	
	2	Birmingham City	2	0.823	
	2	Exeter City	3	0.643	
	3	Exeter City	4	0.639	***0.749***
Coppell, Steve	1	Crystal Palace	1	0.810	
	4	Crystal Palace	2	0.650	
	5	Crystal Palace	2	0.864	
	6	Crystal Palace	1	0.629	***0.738***
Cork, Alan	6	Swansea City	4	0.680	***0.680***
Cox, Arthur	1	Derby County	2	0.783	***0.783***
Crosby, Malcolm	1	Sunderland	2	0.843	***0.843***
Curbishley, Alan	1	Charlton Athletic	2	0.894	
	2	Charlton Athletic	2	0.893	
	3	Charlton Athletic	2	0.882	
	4	Charlton Athletic	2	0.864	
	5	Charlton Athletic	2	0.834	
	6	Charlton Athletic	2	0.905	***0.879***
Dalglish, Kenny	1	Blackburn Rovers	1	0.926	
	2	Blackburn Rovers	1	0.883	
	3	Blackburn Rovers	1	0.891	
	5	Newcastle United	1	0.877	
	6	Newcastle United	1	0.675	***0.850***

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Davies, Fred	2	Shrewsbury Town	4	0.917	
	3	Shrewsbury Town	3	0.880	
	4	Shrewsbury Town	3	0.796	
	5	Shrewsbury Town	3	0.813	***0.852***
Day, Mervyn	4	Carlisle United	3	0.875	
	5	Carlisle United	4	0.869	***0.872***
Deehan, John	2	Norwich City	1	0.345	
	3	Norwich City	1	0.758	
	4	Wigan Athletic	4	0.889	
	5	Wigan Athletic	4	0.891	
	6	Wigan Athletic	3	0.841	***0.745***
Dixon, Kerry	5	Doncaster Rovers	4	0.834	***0.834***
Docherty, John	5	Millwall	3	0.769	***0.769***
Docherty, Mick	3	Rochdale	4	0.691	
	4	Rochdale	4	0.839	***0.765***
Dolan, Terry	1	Hull City	3	0.823	
	2	Hull City	3	0.861	
	3	Hull City	3	0.898	
	4	Hull City	3	0.439	
	5	Hull City	4	0.685	***0.741***
Downs, Greg	1	Hereford United	4	0.811	
	2	Hereford United	4	0.816	***0.813***
Duncan, John	1	Chesterfield	4	0.857	
	2	Chesterfield	4	0.861	
	3	Chesterfield	4	0.880	
	4	Chesterfield	3	0.904	
	5	Chesterfield	3	0.887	
	6	Chesterfield	3	0.785	***0.862***
Ellis, Sam	3	Lincoln City	4	0.845	***0.845***
Eustace, Peter	1	Leyton Orient	3	0.878	
	2	Leyton Orient	3	0.790	***0.834***
Evans, Roy	2	Liverpool	1	0.794	
	3	Liverpool	1	0.849	
	4	Liverpool	1	0.792	
	5	Liverpool	1	0.746	
	6	Liverpool	1	0.778	***0.792***
Fenwick, Terry	3	Portsmouth	2	0.892	
	4	Portsmouth	2	0.814	
	5	Portsmouth	2	0.871	
	6	Portsmouth	2	0.751	***0.832***
Ferguson, Alex	1	Manchester United	1	0.899	
	2	Manchester United	1	0.882	
	3	Manchester United	1	0.868	
	4	Manchester United	1	0.894	
	5	Manchester United	1	0.827	
	6	Manchester United	1	0.852	***0.870***
Flanagan, Mike	2	Gillingham	4	0.840	
	3	Gillingham	4	0.748	***0.794***
Flynn, Brian	1	Wrexham	4	0.919	
	2	Wrexham	3	0.917	
	3	Wrexham	3	0.880	
	4	Wrexham	3	0.871	
	5	Wrexham	3	0.910	
	6	Wrexham	3	0.898	***0.899***
Foster, George	1	Mansfield Town	3	0.834	***0.834***
Fox, Peter	4	Exeter City	4	0.850	
	5	Exeter City	4	0.821	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Fox, Peter (cont.)	6	Exeter City	4	0.769	*0.814*
Francis, Gerry	1	Queens Park Rangers	1	0.886	
	2	Queens Park Rangers	1	0.879	
	3	Queens Park Rangers	1	0.791	
	3	Tottenham Hotspur	1	0.857	
	4	Tottenham Hotspur	1	0.842	
	5	Tottenham Hotspur	1	0.780	
	6	Tottenham Hotspur	1	0.636	*0.810*
Francis, Trevor	1	Sheffield Wednesday	1	0.852	
	2	Sheffield Wednesday	1	0.894	
	3	Sheffield Wednesday	1	0.825	
	5	Birmingham City	2	0.814	
	6	Birmingham City	2	0.790	*0.835*
Fry, Barry	1	Barnet	4	0.930	
	2	Southend United	2	0.927	
	2	Birmingham City	2	0.814	
	3	Birmingham City	3	0.770	
	4	Birmingham City	2	0.847	
	5	Peterborough United	3	0.712	
	6	Peterborough United	4	0.748	*0.821*
Fuccillo, Lil	1	Peterborough United	2	0.911	
	2	Peterborough United	2	0.578	*0.744*
Gemmill, Archie	3	Rotherham United	3	0.855	
	4	Rotherham United	3	0.773	*0.814*
Gorman, John	2	Swindon Town	1	0.477	
	3	Swindon Town	2	0.734	*0.605*
Gould, Bobby	1	Coventry City	1	0.870	
	2	Coventry City	1	0.846	*0.858*
Gradi, Dario	1	Crewe Alexandra	4	0.903	
	2	Crewe Alexandra	4	0.910	
	3	Crewe Alexandra	3	0.942	
	4	Crewe Alexandra	3	0.912	
	5	Crewe Alexandra	3	0.926	
	6	Crewe Alexandra	2	0.932	*0.921*
Graham, George	1	Arsenal	1	0.775	
	2	Arsenal	1	0.849	
	3	Arsenal	1	0.815	
	5	Leeds United	1	0.772	
	6	Leeds United	1	0.818	*0.806*
Green, Bill	1	Scunthorpe United	4	0.818	*0.818*
Gregory, John	5	Wycombe Wanderers	3	0.899	
	6	Wycombe Wanderers	3	0.767	
	6	Aston Villa	1	0.926	*0.864*
Gritt, Steve	5	Brighton and Hove Albion	4	0.831	
	6	Brighton and Hove Albion	4	0.394	*0.612*
Gross, Christen	6	Tottenham Hotspurs	1	0.803	*0.803*
Gullit, Ruud	5	Chelsea	1	0.916	
	6	Chelsea	1	0.917	*0.917*
Halsall, Mick	4	Peterborough United	3	0.799	*0.799*
Hamilton, Bryan	1	Wigan Athletic	3	0.741	*0.741*
Harford, Ray	4	Blackburn Rovers	1	0.750	
	5	Blackburn Rovers	1	0.096	
	5	West Bromwich Albion	2	0.812	
	6	West Bromwich Albion	2	0.891	
	6	Queens Park Rangers	2	0.259	*0.562*
Hateley, Mark	6	Hull City	4	0.776	*0.776*
Heath, Adrian	4	Burnley	3	0.605	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Heath, Adrian (cont.)	5	Burnley	3	0.898	***0.752***
Henson, Phil	1	Rotherham United	3	0.881	
	2	Rotherham United	3	0.851	***0.866***
Hibbitt, Kenny	1	Walsall	4	0.923	
	2	Walsall	4	0.843	
	4	Cardiff City	4	0.756	
	5	Cardiff City	4	0.843	
	6	Cardiff City	4	0.539	***0.781***
Hoddle, Glen	1	Swindon Town	2	0.923	
	2	Chelsea	1	0.884	
	3	Chelsea	1	0.819	
	4	Chelsea	1	0.822	***0.862***
Hodges, Kevin	5	Torquay United	4	0.781	
	6	Torquay United	4	0.929	***0.855***
Hodgson, David	4	Darlington	4	0.840	
	5	Darlington	4	0.810	
	6	Darlington	4	0.728	***0.793***
Hodgson, Roy	6	Blackburn Rovers	1	0.823	***0.823***
Holder, Phil	1	Brentford	2	0.874	***0.874***
Holland, Pat	4	Leyton Orient	4	0.702	
	5	Leyton Orient	4	0.791	***0.746***
Holloway, Ian	5	Bristol Rovers	3	0.904	
	6	Bristol Rovers	3	0.913	***0.909***
Horton, Brian	1	Oxford United	2	0.739	
	2	Manchester City	1	0.620	
	3	Manchester City	1	0.766	
	4	Huddersfield Town	2	0.892	
	5	Huddersfield Town	2	0.636	
	6	Brighton and Hove Albion	4	0.607	***0.710***
Houchen, Keith	4	Hartlepool United	4	0.732	
	5	Hartlepool United	4	0.727	***0.730***
Houston, Stewart	5	Queens Park Rangers	2	0.717	
	6	Queens Park Rangers	2	0.762	***0.740***
Jackett, Kenny	5	Watford	3	0.799	***0.799***
Jackson, Peter	6	Huddersfield Town	2	0.838	***0.838***
Jewell, Paul	6	Bradford City	2	0.816	***0.816***
Johnson, Gary	2	Cambridge United	3	0.867	
	3	Cambridge United	3	0.728	***0.797***
Jones, Dave	4	Stockport County	3	0.859	
	5	Stockport County	3	0.920	
	6	Southampton	1	0.854	***0.878***
Jones, Mick	6	Plymouth Argyle	3	0.676	***0.676***
Jordan, Joe	2	Stoke City	2	0.903	
	3	Bristol Rovers	2	0.702	
	4	Bristol City	3	0.695	
	5	Bristol City	3	0.914	***0.804***
Kamara, Chris	4	Bradford City	3	0.893	
	5	Bradford City	2	0.844	
	6	Bradford City	2	0.839	
	6	Stoke City	2	0.261	***0.709***
Keegan, Kevin	1	Newcastle United	2	0.915	
	2	Newcastle United	1	0.932	
	3	Newcastle United	1	0.873	
	4	Newcastle United	1	0.921	
	5	Newcastle United	1	0.894	***0.907***
Kendall, Howard	1	Everton	1	0.851	
	2	Everton	1	0.869	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Kendall, Howard (cont.)	3	Notts County	2	0.769	
	4	Sheffield United	2	0.828	
	5	Sheffield United	2	0.710	
	6	Everton	1	0.651	*0.780*
King, Andy	2	Mansfield Town	4	0.722	
	3	Mansfield Town	4	0.784	
	4	Mansfield Town	4	0.606	*0.704*
King, John	1	Tranmere Rovers	2	0.913	
	2	Tranmere Rovers	2	0.922	
	3	Tranmere Rovers	2	0.917	
	4	Tranmere Rovers	2	0.865	*0.904*
King, Jake	6	Shrewsbury Town	4	0.784	*0.784*
Kinnear, Joe	1	Wimbledon	1	0.824	
	2	Wimbledon	1	0.869	
	3	Wimbledon	1	0.852	
	4	Wimbledon	1	0.787	
	5	Wimbledon	1	0.878	
	6	Wimbledon	1	0.745	*0.826*
Lawrence, Lennie	1	Middlesbrough	1	0.822	
	2	Middlesbrough	2	0.717	
	3	Bradford City	3	0.783	
	4	Bradford City	3	0.836	
	4	Luton Town	2	0.786	
	5	Luton Town	3	0.865	
	6	Luton Town	3	0.729	*0.791*
Laws, Brian	3	Grimsby Town	2	0.871	
	4	Grimsby Town	2	0.804	
	5	Grimsby Town	2	0.678	
	5	Scunthorpe United	4	0.883	
	6	Scunthorpe United	4	0.858	*0.819*
Layton, John	3	Hereford United	4	0.847	*0.847*
Little, Alan	1	York City	4	0.932	
	2	York City	3	0.911	
	3	York City	3	0.866	
	4	York City	3	0.701	
	5	York City	3	0.866	
	6	York City	3	0.796	*0.845*
Little, Brian	1	Leicester City	2	0.907	
	2	Leicester City	2	0.901	
	3	Leicester City	1	0.666	
	3	Aston Villa	1	0.819	
	4	Aston Villa	1	0.837	
	5	Aston Villa	1	0.820	
	6	Aston Villa	1	0.652	*0.800*
Livermore, Doug	1	Tottenham Hotspurs	1	0.855	*0.855*
Lloyd, Barry	1	Brighton and Hove Albion	3	0.847	
	2	Brighton and Hove Albion	3	0.658	*0.753*
Lyall, John	3	Ipswich Town	1	0.676	*0.676*
Macari, Lou	1	Stoke City	3	0.900	
	2	Stoke City	2	0.908	
	3	Stoke City	2	0.867	
	4	Stoke City	2	0.889	
	5	Stoke City	2	0.893	*0.891*
McCall, Steve	3	Plymouth Argyle	3	0.594	*0.594*
McCarthy, Mick	1	Millwall	2	0.899	
	2	Millwall	2	0.929	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
McCarthy, Mick (cont.)	3	Millwall	2	0.903	
	4	Millwall	2	0.880	***0.903***
McCreery, Dave	1	Carlisle United	4	0.825	
	3	Hartlepool United	4	0.796	***0.811***
McDonough, Roy	1	Colchester United	4	0.925	
	2	Colchester United	4	0.780	***0.853***
McEwan, Billy	1	Darlington	4	0.774	***0.774***
McFarland, Roy	2	Derby County	2	0.780	
	3	Derby County	2	0.845	
	4	Bolton Wanderers	1	0.356	
	5	Cambridge United	4	0.743	
	6	Cambridge United	4	0.746	***0.694***
McGhee, Mark	1	Reading	3	0.900	
	2	Reading	3	0.924	
	3	Reading	2	0.940	
	3	Leicester City	1	0.545	
	4	Leicester City	2	0.835	
	4	Wolverhampton Wanderers	2	0.812	
	5	Wolverhampton Wanderers	2	0.865	
	6	Wolverhampton Wanderers	2	0.810	***0.829***
McGiven, Mick	1	Ipswich Town	1	0.893	
	2	Ipswich Town	1	0.732	***0.813***
McGrath, John	1	Halifax Town	4	0.783	***0.783***
McHale, Ray	1	Scarborough	4	0.873	
	3	Scarborough	4	0.574	
	4	Scarborough Town	4	0.689	***0.712***
Machin, Mel	1	Barnsley	2	0.829	
	3	Bournemouth	3	0.787	
	4	Bournemouth	3	0.851	
	5	Bournemouth	3	0.875	
	6	Bournemouth	3	0.806	***0.830***
McIlroy, Sammy	6	Macclesfield Town	4	0.903	***0.903***
Mackay,Don	1	Fulham	3	0.810	
	2	Fulham	3	0.796	***0.803***
McMahon, Steve	3	Swindon Town	2	0.540	
	4	Swindon Town	3	0.825	
	5	Swindon Town	2	0.901	
	6	Swindon Town	2	0.817	***0.771***
McMenemy, Chris	1	Chesterfield	4	0.832	***0.832***
McNally, Harry	1	Chester City	3	0.410	***0.410***
MacPhail, Joe	2	Hartlepool United	3	0.762	***0.762***
Mann, Derek	3	Chester City	3	0.286	***0.286***
Martin, Alvin	6	Southend United	3	0.608	***0.608***
May, Eddie	1	Cardiff City	4	0.856	
	2	Cardiff City	3	0.783	
	3	Cardiff City	3	0.764	
	4	Torquay United	4	0.357	***0.690***
Megson, Gary	4	Norwich City	2	0.469	
	5	Blackpool	3	0.883	
	6	Stockport County	2	0.897	***0.749***
Merrington, Dave	4	Southampton	1	0.626	***0.626***
Molby, Jan	4	Swansea City	3	0.888	
	5	Swansea City	4	0.819	
	6	Swansea City	4	0.798	***0.835***
Money, Richard	1	Scunthorpe United	4	0.804	
	2	Scunthorpe United	4	0.761	***0.782***

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Moore, David	3	Scunthorpe United	4	0.865	
	4	Scunthorpe United	4	0.668	*0.766*
Moore, Ronnie	6	Rotherham United	4	0.712	*0.712*
Moyes, David	6	Preston North End	3	0.723	*0.723*
Mullen, Jimmy	1	Burnley	3	0.853	
	2	Burnley	3	0.858	
	3	Burnley	2	0.793	
	4	Burnley	3	0.753	*0.814*
Mullery, Alan	5	Barnet	4	0.760	*0.760*
Murphy, Colin	1	Southend United	2	0.602	*0.602*
Murray, Alan	1	Hartlepool United	3	0.902	
	2	Darlington	4	0.859	
	3	Darlington	4	0.780	*0.847*
Neal, Phil	2	Coventry City	1	0.896	
	3	Coventry City	1	0.824	
	4	Cardiff City	4	0.679	
	5	Cardiff City	4	0.879	*0.819*
Nicholl, Chris	3	Walsall	4	0.923	
	4	Walsall	3	0.920	
	5	Walsall	3	0.928	*0.924*
Nicholl, Jimmy	4	Millwall	2	0.653	
	5	Millwall	3	0.898	*0.776*
O'Neill, Martin	2	Wycombe Wanderers	4	0.937	
	3	Wycombe Wanderers	3	0.926	
	4	Norwich City	2	0.815	
	4	Leicester City	2	0.796	
	5	Leicester City	1	0.912	
	6	Leicester City	1	0.868	*0.876*
O'Riordan, Don	1	Torquay United	4	0.866	
	2	Torquay United	4	0.902	
	3	Torquay United	4	0.875	
	4	Torquay United	4	0.601	*0.811*
Osman, Russell	1	Bristol City	2	0.908	
	2	Bristol City	2	0.861	
	3	Bristol City	2	0.728	*0.832*
Parkin, Steve	5	Mansfield Town	4	0.867	
	6	Mansfield Town	4	0.800	*0.834*
Pejic, Mike	3	Chester City	3	0.586	*0.586*
Perryman, Steve	1	Watford	2	0.734	*0.734*
Peters, Gary	3	Preston North End	4	0.888	
	4	Preston North End	4	0.851	
	5	Preston North End	3	0.880	
	6	Preston North End	3	0.767	*0.846*
Phillips, Gary	2	Barnet	3	0.618	*0.618*
Philpotts, Dave	1	Wigan Athletic	3	0.566	*0.566*
Platt, Jim	4	Darlington	4	0.896	
	5	Darlington	4	0.635	*0.765*
Pleat, David	1	Luton Town	2	0.626	
	2	Luton Town	2	0.851	
	3	Luton Town	2	0.856	
	4	Sheffield Wednesday	1	0.799	
	5	Sheffield Wednesday	1	0.789	
	6	Sheffield Wednesday	1	0.396	*0.719*
Porterfield, Ian	1	Chelsea	1	0.774	*0.774*
Pulis, Tony	1	Bournemouth	3	0.848	
	2	Bournemouth	3	0.725	
	4	Gillingham	4	0.900	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Pulis, Tony	5	Gillingham	3	0.928	
	6	Gillingham	3	0.886	*0.857*
Quinn, Jimmy	3	Reading	2	0.951	
	4	Reading	2	0.863	
	5	Reading	2	0.890	*0.901*
Ratcliffe, Kevin	4	Chester City	4	0.839	
	5	Chester City	4	0.885	
	6	Chester City	4	0.862	*0.862*
Rathbone, Mick	1	Halifax Town	4	0.603	*0.603*
Redknapp, Harry	3	West Ham United	1	0.797	
	4	West Ham United	1	0.857	
	5	West Ham United	1	0.749	
	6	West Ham United	1	0.836	*0.810*
Reid, Peter	1	Manchester City	1	0.839	
	4	Sunderland	2	0.894	
	5	Sunderland	1	0.887	
	6	Sunderland	2	0.818	*0.860*
Rioch, Bruce	1	Bolton Wanderers	3	0.891	
	2	Bolton Wanderers	2	0.891	
	3	Bolton Wanderers	2	0.864	
	4	Arsenal	1	0.850	*0.874*
Robson, Bryan	3	Middlesbrough	2	0.908	
	4	Middlesbrough	1	0.880	
	5	Middlesbrough	1	0.750	
	6	Middlesbrough	2	0.897	*0.859*
Roeder, Glen	1	Gillingham	4	0.785	
	2	Watford	2	0.849	
	3	Watford	2	0.847	
	4	Watford	2	0.514	*0.749*
Rofe, Dennis	1	Bristol Rovers	2	0.428	*0.428*
Ross, Ian	1	Huddersfield Town	3	0.822	*0.822*
Royle, Joe	1	Oldham Athletic	1	0.848	
	2	Oldham Athletic	1	0.721	
	3	Oldham Athletic	2	0.747	
	3	Everton	1	0.844	
	4	Everton	1	0.869	
	5	Everton	1	0.701	
	6	Manchester City	2	0.732	*0.780*
Rudge, John	1	Port Vale	3	0.868	
	2	Port Vale	3	0.915	
	3	Port Vale	2	0.891	
	4	Port Vale	2	0.835	
	5	Port Vale	2	0.880	
	6	Port Vale	2	0.837	*0.871*
Sharp, Graeme	3	Oldham Athletic	2	0.788	
	4	Oldham Athletic	2	0.843	
	5	Oldham Athletic	2	0.700	*0.777*
Shilton, Peter	1	Plymouth Argyle	3	0.806	
	2	Plymouth Argyle	3	0.918	
	3	Plymouth Argyle	3	0.784	*0.836*
Shotton, Malcolm	6	Oxford United	2	0.900	*0.900*
Slade, Richard	3	Notts County	2	0.574	*0.574*
Smillie, Neil	3	Gillingham	4	0.862	
	6	Wycombe Wanderers	3	0.895	*0.878*
Smith, Alan	2	Crystal Palace	2	0.774	
	3	Crystal Palace	1	0.795	
	4	Wycombe Wanderers	3	0.825	*0.798*

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Smith, Denis	1	Bristol City	2	0.792	
	2	Oxford United	2	0.769	
	3	Oxford United	3	0.775	
	4	Oxford United	3	0.880	
	5	Oxford United	2	0.894	
	6	Oxford United	2	0.795	
	6	West Bromwich Albion	2	0.449	*0.765*
Smith, Jim	1	Portsmouth	2	0.901	
	2	Portsmouth	2	0.782	
	3	Portsmouth	2	0.681	
	4	Derby County	2	0.798	
	5	Derby County	1	0.812	
	6	Derby County	1	0.830	*0.801*
Souness, Graeme	1	Liverpool	1	0.881	
	2	Liverpool	1	0.900	
	5	Southampton	1	0.691	*0.824*
Spackman, Nigel	6	Sheffield United	2	0.827	*0.827*
Stapleton, Frank	1	Bradford City	3	0.889	
	2	Bradford City	3	0.900	*0.894*
Still, John	3	Peterborough United	3	0.719	
	4	Peterborough United	3	0.704	
	6	Barnet	4	0.787	*0.737*
Strachan, Gordon	5	Coventry City	1	0.819	
	6	Coventry City	1	0.783	*0.801*
Sutton, Dave	1	Rochdale United	4	0.877	
	2	Rochdale United	4	0.867	
	3	Rochdale United	4	0.885	*0.876*
Swain, Kenny	2	Wigan Athletic	4	0.796	
	5	Grimsby Town	2	0.759	*0.777*
Tait, Mick	5	Hartlepool United	4	0.772	
	6	Hartlepool United	4	0.661	*0.716*
Taylor, Graham	2	Wolverhampton Wanderers	2	0.872	
	3	Wolverhampton Wanderers	2	0.851	
	4	Wolverhampton Wanderers	2	0.706	
	6	Watford	3	0.882	*0.827*
Taylor, Peter	2	Southend United	2	0.838	
	3	Southend United	2	0.807	*0.823*
Taylor, Tommy	4	Cambridge United	4	0.738	
	5	Cambridge United	4	0.914	
	5	Leyton Orient	4	0.797	
	6	Leyton Orient	4	0.823	*0.818*
Ternent, Stan	4	Bury	4	0.877	
	5	Bury	3	0.926	
	6	Bury	2	0.769	*0.857*
Thompson, Steve	1	Lincoln City	4	0.891	
	3	Southend United	2	0.921	
	4	Notts County	3	0.878	
	5	Notts County	3	0.789	*0.870*
Todd, Colin	4	Bolton Wanderers	1	0.886	
	5	Bolton Wanderers	2	0.797	
	6	Bolton Wanderers	1	0.707	*0.797*
Turner, Chris	1	Peterborough United	2	0.931	
	3	Leyton Orient	3	0.581	*0.756*
Turner, Graham	1	Wolverhampton Wanderers	2	0.819	
	2	Wolverhampton Wanderers	2	0.788	
	4	Hereford United	4	0.869	
	5	Hereford United	4	0.677	*0.788*

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Vialli, Gianluca	6	Chelsea	1	0.904	*0.904*
Waddle, Chris	6	Burnley	3	0.668	*0.668*
Wadsworth, Mick	2	Carlisle United	4	0.869	
	3	Carlisle United	4	0.909	
	4	Carlisle United	3	0.724	
	5	Scarborough	4	0.829	
	6	Scarborough	4	0.842	*0.834*
Walker,Mick	1	Notts County	2	0.837	
	2	Notts County	2	0.884	*0.861*
Walker, Mike	1	Norwich City	1	0.904	
	2	Norwich City	1	0.868	
	2	Everton	1	0.773	
	3	Everton	1	0.243	
	5	Norwich City	2	0.807	
	6	Norwich City	2	0.788	*0.731*
Walsh, Mike	1	Bury	4	0.844	
	2	Bury	4	0.830	
	3	Bury	4	0.915	*0.863*
Ward, John	1	York City	4	0.898	
	1	Bristol Rovers	2	0.620	
	2	Bristol Rovers	3	0.757	
	3	Bristol Rovers	3	0.880	
	4	Bristol Rovers	3	0.851	
	6	Bristol City	3	0.879	*0.814*
Warnock, Neil	1	Notts County	2	0.555	
	2	Huddersfield Town	3	0.867	
	3	Huddersfield Town	3	0.854	
	4	Plymouth Argyle	4	0.798	
	5	Plymouth Argyle	3	0.094	
	5	Oldham Athletic	2	0.726	
	6	Oldham Athletic	3	0.695	*0.655*
Weaver, Mark	6	Doncaster Rovers	4	0.469	*0.469*
Webb, David	1	Chelsea	1	0.871	
	2	Brentford	3	0.592	
	3	Brentford	3	0.883	
	4	Brentford	3	0.748	
	5	Brentford	3	0.887	
	6	Brentford	3	0.767	*0.791*
Wenger, Arsene	5	Arsenal	1	0.903	
	6	Arsenal	1	0.921	*0.912*
Westley, Terry	4	Luton Town	2	0.627	*0.627*
Whelan, Ronnie	4	Southend United	2	0.849	
	5	Southend United	2	0.640	*0.744*
Wicks, Steve	2	Scarborough	4	0.904	*0.904*
Wignall, Steve	3	Colchester United	4	0.858	
	4	Colchester United	4	0.874	
	5	Colchester United	4	0.830	
	6	Colchester United	4	0.868	*0.857*
Wilkes, David	6	Carlisle United	3	0.814	*0.814*
Wilkins, Ray	3	Queens Park Rangers	1	0.932	
	4	Queens Park Rangers	1	0.855	
	6	Fulham	3	0.775	*0.854*
Wilkinson, Howard	1	Leeds United	1	0.643	
	2	Leeds United	1	0.773	
	3	Leeds United	1	0.859	
	4	Leeds United	1	0.835	*0.778*
Wilson, Danny	3	Barnsley	2	0.897	

Manager Name	Time Period	Club Name	Division	Efficiency	Av. Efficiency
Wilson, Danny (cont.)	4	Barnsley	2	0.809	
	5	Barnsley	2	0.891	
	6	Barnsley	1	0.857	***0.864***
Worthington, Nigel	6	Blackpool	3	0.814	***0.814***
Yorath, Terry	3	Cardiff City	3	0.627	***0.627***

Notes: **Time period one refers to football season 1992/93, time-period two refers to football season 1993/94 and so on.**
Divisions 1-4 based on old classification (i.e., prior to Premier League). Division 1 refers to the Premier League; Division 2 refers to Football League Division 1; Division 3 refers to Football League Division 2; and Division 4 refers to Football League Division 3.
For joint managerial positions only the manager who remained with the club in the long term is recorded.
Efficiency scores can be converted into percentage form by multiplying by 100.

DATA APPENDIX

League performance and team quality data (based on "average" player valuation) are presented below for each manager in club order by time period (season).

Club Name	Manager Name	Time Period	Division	Matches	Weight	W	L	D	Valuation (£)
Arsenal	Graham, George	1	1	42	1	15	16	11	2,438,335
	Graham, George	2	1	42	1	18	7	17	2,194,433
	Graham, George	3	1	29	0.691	9	10	10	1,932,642
	Rioch, Bruce	4	1	38	1	17	9	12	2,204,033
	Wenger, Arsene	5	1	33	0.868	17	7	9	1,819,654
	Wenger, Arsene	6	1	38	1	23	6	9	1,743,998
Aston Villa	Atkinson, Ron	1	1	42	1	21	10	11	1,784,069
	Atkinson, Ron	2	1	42	1	15	15	12	1,797,101
	Atkinson, Ron	3	1	14	0.333	2	8	4	1,720,358
	Little, Brian	3	1	27	0.643	8	8	11	1,720,358
	Little, Brian	4	1	38	1	18	11	9	2,484,591
	Little, Brian	5	1	38	1	17	11	10	2,462,432
	Little, Brian	6	1	27	0.711	8	13	6	2,540,762
	Gregory, John	6	1	11	0.290	9	2	0	2,540,762
Barnet	Fry, Barry	1	4	38	0.905	22	7	9	35,097
	Phillips, Gary	2	3	22	0.478	2	16	4	48,933
	Clemence, Ray	2	3	23	0.5	3	11	9	48,933
	Clemence, Ray	3	4	42	1	15	16	11	55,364
	Clemence, Ray	4	4	46	1	18	12	16	38,236
	Mullery, Alan	5	4	36	0.783	10	11	15	36,589
	Bullivant, Terry	5	4	10	0.217	4	5	1	36,589
	Still, John	6	4	46	1	19	14	13	48,850
Barnsley	Machin, Mel	1	2	45	0.9783	16	20	9	464,609
	Anderson, Viv	2	2	46	1	16	23	7	456,121
	Wilson, Danny	3	2	46	1	20	14	12	397,577
	Wilson, Danny	4	2	46	1	14	14	18	418,799
	Wilson, Danny	5	2	46	1	22	10	14	419,468
	Wilson, Danny	6	1	38	1	10	23	5	1,428,593
Birmingham City	Cooper, Terry	1	2	46	1	13	21	12	297,773
	Cooper, Terry	2	2	18	0.391	5	8	5	423,208
	Fry, Barry	2	2	27	0.587	8	12	7	423,208
	Fry, Barry	3	3	46	1	25	7	14	148,999
	Fry, Barry	4	2	46	1	15	18	13	356,419
	Francis, Trevor	5	2	46	1	17	14	15	479,604
	Francis, Trevor	6	2	46	1	19	10	17	579,310
Blackburn Rovers	Dalglish, Kenny	1	1	42	1	20	11	11	1,547,957
	Dalglish, Kenny	2	1	42	1	25	8	9	2,582,270
	Dalglish, Kenny	3	1	42	1	27	7	8	2,667,913
	Harford, Ray	4	1	38	1	18	13	7	2,814,837
	Harford, Ray	5	1	10	0.263	0	6	4	2,512,139
	Hodgson, Roy	6	1	38	1	16	12	10	2,209,056

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Blackpool	Ayre, Billy	1	3	46	1	12	19	15	56,438
	Ayre, Billy	2	3	46	1	16	25	5	75,092
	Allardyce, Sam	3	3	46	1	18	18	10	98,944
	Allardyce, Sam	4	3	46	1	23	10	13	98,677
	Megson, Gary	5	3	46	1	18	13	15	96,267
	Worthington, Nigel	6	3	46	1	17	18	11	111,233
Bolton Wanderers	Rioch, Bruce	1	3	46	1	27	10	9	111,627
	Rioch, Bruce	2	2	46	1	15	17	14	325,689
	Rioch, Bruce	3	2	46	1	21	11	14	466,993
	McFarland, Roy	4	1	22	0.579	2	16	4	1,634,473
	Todd, Colin	4	1	16	0.421	6	9	1	1,634,473
	Todd, Colin	5	2	46	1	28	4	14	665,422
	Todd, Colin	6	1	38	1	9	16	13	1,692,713
Bournemouth	Pulis, Tony	1	3	46	1	12	17	17	68,558
	Pulis, Tony	2	3	46	1	14	17	15	105,796
	Machin, Mel	3	3	42	0.913	13	18	11	88,589
	Machin, Mel	4	3	46	1	16	20	10	83,867
	Machin, Mel	5	3	46	1	15	16	15	85,522
	Machin, Mel	6	3	46	1	18	16	12	107,169
Bradford City	Stapleton, Frank	1	3	46	1	18	14	14	91,731
	Stapleton, Frank	2	3	45	0.978	18	14	13	83,609
	Lawrence, Lennie	3	3	46	1	16	18	12	96,877
	Lawrence, Lennie	4	3	18	0.391	7	7	4	105,928
	Kamara, Chris	4	3	28	0.609	15	10	3	105,928
	Kamara, Chris	5	2	46	1	12	22	12	288,138
	Kamara, Chris	6	2	25	0.544	8	7	10	384,343
	Jewell, Paul	6	2	18	0.391	5	9	4	384,343
Brentford	Holder, Phil	1	2	46	1	13	23	10	323,333
	Webb, David	2	3	46	1	13	14	19	117,581
	Webb, David	3	3	46	1	25	11	10	99,526
	Webb, David	4	3	46	1	15	18	13	104,428
	Webb, David	5	3	46	1	20	12	14	101,383
	Webb, David	6	3	16	0.348	4	8	4	86,608
	Adams, Micky	6	3	30	0.652	7	10	13	86,608
Brighton	Lloyd, Barry	1	3	46	1	20	17	9	109,570
	Lloyd, Barry	2	3	18	0.391	3	9	6	77,499
	Brady, Liam	2	3	27	0.587	12	8	7	77,499
	Brady, Liam	3	3	46	1	14	15	17	83,933
	Brady, Liam	4	3	17	0.370	3	11	3	82,157
	Case, Jimmy	4	3	29	0.630	7	15	7	82,157
	Case, Jimmy	5	4	22	0.478	3	15	4	45,675
	Gritt, Steve	5	4	24	0.522	10	8	6	45,675
	Gritt, Steve	6	4	34	0.739	4	19	11	36,978
	Horton, Brian	6	4	12	0.261	2	4	6	36,978
Bristol City	Smith, Denis	1	2	25	0.544	7	12	6	440,723
	Osman, Russell	1	2	12	0.261	5	2	5	440,723
	Osman, Russell	2	2	46	1	16	14	16	425,872
	Osman, Russell	3	2	16	0.348	4	8	4	467,658
	Jordan, Joe	3	2	30	0.652	7	15	8	467,658
	Jordan, Joe	4	3	46	1	15	16	15	133,798
	Jordan, Joe	5	3	37	0.804	15	13	9	90,981
	Ward, John	6	3	46	1	25	11	10	102,886
Bristol Rovers	Rofe, Dennis	1	2	17	0.367	2	12	3	436,001
	Ward, John	1	2	12	0.261	2	5	5	436,001
	Ward, John	2	3	46	1	20	16	10	129,257
	Ward, John	3	3	46	1	22	8	16	92,657

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Bristol Rovers (cont.)	Ward, John	4	3	28	0.609	11	9	8	98,809
	Holloway, Ian	5	3	46	1	15	20	11	76,116
	Holloway, Ian	6	3	46	1	20	16	10	74,248
Burnley	Mullen, Jimmy	1	3	46	1	15	15	16	79,417
	Mullen, Jimmy	2	3	46	1	21	15	10	101,341
	Mullen, Jimmy	3	2	46	1	11	22	13	341,658
	Mullen, Jimmy	4	3	27	0.587	10	9	8	129,034
	Heath, Adrian	4	3	16	0.348	4	8	4	129,034
	Heath, Adrian	5	3	46	1	19	16	11	96,299
	Waddle, Chris	6	3	46	1	13	20	13	119,545
Bury	Walsh, Mike	1	4	42	1	18	15	9	54,311
	Walsh, Mike	2	4	42	1	14	17	11	45,686
	Walsh, Mike	3	4	42	1	23	8	11	43,412
	Ternent, Stan	4	4	41	0.891	21	9	11	41,887
	Ternent, Stan	5	3	46	1	24	10	12	82,121
	Ternent, Stan	6	2	46	1	11	16	19	316,952
Cambridge United	Beck, John	1	2	12	0.261	3	6	3	433,603
	Atkins, Ian	1	2	27	0.587	7	10	10	433,603
	Johnson, Gary	2	3	46	1	19	18	9	90,227
	Johnson, Gary	3	3	40	0.870	8	18	14	71,709
	Taylor, Tommy	4	4	46	1	14	20	12	40,583
	Taylor, Tommy	5	4	17	0.370	10	4	3	38,562
	McFarland, Roy	5	4	29	0.630	8	13	8	38,562
	McFarland, Roy	6	4	46	1	14	14	18	41,856
Cardiff City	May, Eddie	1	4	42	1	25	9	8	59,074
	May, Eddie	2	3	46	1	13	18	15	78,699
	May, Eddie	3	3	18	0.391	4	10	4	72,792
	Yorath, Terry	3	3	20	0.435	3	12	5	72,792
	Hibbitt, Kenny	4	4	19	0.413	6	8	5	43,625
	Neal, Phil	4	4	21	0.457	5	12	4	43,625
	Neal, Phil	5	4	10	0.217	4	4	2	40,750
	Hibbitt, Kenny	5	4	25	0.544	10	10	5	40,750
	Hibbitt, Kenny	6	4	31	0.674	6	8	17	42,047
	Burrows, Frank	6	4	15	0.326	3	6	6	42,047
Carlisle United	McCreery, David	1	4	34	0.810	9	15	10	39,914
	Wadsworth, Mick	2	4	42	1	18	14	10	44,092
	Wadsworth, Mick	3	4	42	1	27	5	10	47,633
	Wadsworth, Mick	4	3	25	0.544	5	11	9	77,734
	Day, Mervyn	4	3	21	0.457	7	10	4	77,734
	Day, Mervyn	5	4	46	1	24	10	12	44,636
	Wilkes, David	6	3	40	0.87	11	22	7	82,189
Charlton Athletic	Curbishley, Alan	1	2	46	1	16	17	13	365,257
	Curbishley, Alan	2	2	46	1	19	19	8	422,153
	Curbishley, Alan	3	2	46	1	16	19	11	349,014
	Curbishley, Alan	4	2	46	1	17	9	20	402,150
	Curbishley, Alan	5	2	46	1	16	19	11	405,418
	Curbishley, Alan	6	2	46	1	26	10	10	444,042
Chelsea	Porterfield, Ian	1	1	29	0.691	9	10	10	2,001,825
	Webb, David	1	1	13	0.310	5	4	4	2,001,825
	Hoddle, Glenn	2	1	42	1	13	17	12	1,447,641
	Hoddle, Glenn	3	1	42	1	13	14	15	1,920,861
	Hoddle, Glenn	4	1	38	1	12	12	14	2,025,969
	Gullit, Ruud	5	1	38	1	16	11	11	1,610,786
	Gullit, Ruud	6	1	25	0.658	14	8	3	2,126,409
	Vialli, Gianluca	6	1	13	0.342	6	7	0	2,126,409
Chester City	McNally, Harry	1	3	11	0.239	1	8	2	73,578

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Chester (cont.)	Barrow, Graham	1	3	30	0.652	5	24	1	73,578
	Barrow, Graham	2	4	42	1	21	10	11	46,742
	Pejic, Mike	3	3	24	0.522	3	17	4	59,804
	Mann, Derek	3	3	18	0.391	1	10	7	59,804
	Ratcliffe, Kevin	4	4	46	1	18	12	16	47,365
	Ratcliffe, Kevin	5	4	46	1	18	12	16	37,017
	Ratcliffe, Kevin	6	4	46	1	17	19	10	41,490
Chesterfield	McMenemy, Chris	1	4	26	0.619	9	10	7	46,694
	Duncan, John	1	4	16	0.381	6	6	4	46,694
	Duncan, John	2	4	42	1	16	12	14	42,506
	Duncan, John	3	4	42	1	23	7	12	51,764
	Duncan, John	4	3	46	1	20	14	12	80,832
	Duncan, John	5	3	46	1	18	14	14	100,072
	Duncan, John	6	3	46	1	16	13	17	108,286
Colchester United	McDonough, Roy	1	4	42	1	18	19	5	30,992
	McDonough, Roy	2	4	42	1	13	19	10	48,623
	Burley, George	3	4	19	0.452	9	5	5	38,408
	Wignall, Steve	3	4	19	0.452	6	9	4	38,408
	Wignall, Steve	4	4	46	1	18	10	18	35,973
	Wignall, Steve	5	4	46	1	17	12	17	39,711
	Wignall, Steve	6	4	46	1	21	14	11	43,314
Coventry City	Gould, Bobby	1	1	42	1	13	16	13	1,486,089
	Gould, Bobby	2	1	12	0.286	3	3	6	1,489,872
	Neal, Phil	2	1	27	0.643	10	11	6	1,489,872
	Neal, Phil	3	1	28	0.667	7	11	10	1,466,730
	Atkinson, Ron	3	1	14	0.333	5	5	4	1,466,730
	Atkinson, Ron	4	1	38	1	8	16	14	1,538,747
	Atkinson, Ron	5	1	12	0.316	1	5	6	1,965,108
	Strachan, Gordon	5	1	26	0.684	8	10	8	1,965,108
	Strachan, Gordon	6	1	38	1	12	10	16	2,103,375
Crewe Alexandra	Gradi, Dario	1	4	42	1	21	14	7	43,593
	Gradi, Dario	2	4	42	1	21	11	10	44,158
	Gradi, Dario	3	3	46	1	25	13	8	63,745
	Gradi, Dario	4	3	46	1	22	17	7	88,634
	Gradi, Dario	5	3	46	1	22	17	7	92,051
	Gradi, Dario	6	2	46	1	18	5	23	264,406
Crystal Palace	Coppell, Steve	1	1	42	1	11	15	16	1,890,093
	Smith, Alan	2	2	46	1	27	10	9	828,796
	Smith, Alan	3	1	42	1	11	19	12	1,514,570
	Coppell, Steve	4	2	26	0.565	8	7	11	626,054
	Bassett, Dave	4	2	20	0.435	12	4	4	626,054
	Bassett, Dave	5	2	32	0.696	13	9	10	523,688
	Coppell, Steve	5	2	11	0.239	5	3	3	523,688
	Coppell, Steve	6	1	28	0.737	5	15	8	1,740,067
Darlington	McEwan, Billy	1	4	42	1	12	16	14	42,379
	Murray, Alan	2	4	30	0.714	10	14	6	37,923
	Murray, Alan	3	4	29	0.691	10	13	6	49,076
	Hodgson, David	4	4	18	0.391	6	4	8	39,186
	Platt, Jim	4	4	27	0.587	13	4	10	39,186
	Platt, Jim	5	4	18	0.391	4	10	4	41,767
	Hodgson, David	5	4	28	0.609	10	12	6	41,767
	Hodgson, David	6	4	46	1	14	20	12	44,003
Derby County	Cox, Arthur	1	2	46	1	19	18	9	643,983
	McFarland, Roy	2	2	38	0.826	17	12	9	687,823
	McFarland, Roy	3	2	45	0.978	18	15	12	456,738
	Smith, Jim	4	2	46	1	21	9	16	514,491

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Derby (cont.)	Smith, Jim	5	1	38	1	11	14	13	1,541,965
	Smith, Jim	6	1	38	1	16	15	7	2,019,411
Doncaster Rovers	Beaglehole, Steve	1	4	42	1	11	17	14	41861
	Beaglehole, Steve	2	4	18	0.429	8	8	2	42,037
	Atkins, Ian	2	4	19	0.452	6	6	7	42,037
	Chung, Sammy	3	4	42	1	17	15	10	38,737
	Chung, Sammy	4	4	46	1	16	19	11	38,689
	Dixon, Kerry	5	4	46	1	14	22	10	34,167
	Weaver, Mark	6	4	32	0.696	4	24	4	31,923
Everton	Kendall, Howard	1	1	42	1	15	19	8	1,798,108
	Kendall, Howard	2	1	18	0.429	7	8	3	1,867,490
	Walker, Mike	2	1	17	0.405	5	8	4	1,867,490
	Walker, Mike	3	1	14	0.333	1	8	5	1,777,289
	Royle, Joe	3	1	28	0.667	10	6	12	1,777,289
	Royle, Joe	4	1	38	1	17	11	10	1,977,941
	Royle, Joe	5	1	31	0.816	9	13	9	2,170,784
	Kendall, Howard	6	1	38	1	9	16	13	1,780,963
Exeter City	Ball, Alan	1	3	46	1	11	18	17	76,829
	Ball, Alan	2	3	22	0.478	6	9	7	92,815
	Cooper, Terry	2	3	23	0.5	5	13	5	92,815
	Cooper, Terry	3	4	42	1	8	24	10	38,012
	Fox, Peter	4	4	46	1	13	15	18	30,663
	Fox, Peter	5	4	46	1	12	22	12	30,504
	Fox, Peter	6	4	46	1	15	16	15	44,749
Fulham	Mackay, Don	1	3	46	1	16	13	17	92,612
	Mackay, Don	2	3	37	0.804	12	18	7	88,780
	Branfoot, Ian	3	4	42	1	16	12	14	40,771
	Branfoot, Ian	4	4	29	0.630	5	10	14	41,585
	Adams, Micky	4	4	17	0.370	7	7	3	41,585
	Adams, Micky	5	4	46	1	25	9	12	32,788
	Wilkins, Ray	6	3	38	0.826	17	13	8	147,793
Gillingham	Roeder, Glenn	1	4	31	0.738	8	14	9	38,595
	Flanagan, Mike	2	4	42	1	12	15	15	34,568
	Flanagan, Mike	3	4	31	0.738	7	17	7	36,198
	Smillie, Neil	3	4	11	0.262	3	4	4	36,198
	Pulis, Tony	4	4	46	1	22	7	17	37,823
	Pulis, Tony	5	3	46	1	19	17	10	71,713
	Pulis, Tony	6	3	46	1	19	14	13	85,259
Grimsby Town	Buckley, Alan	1	2	46	1	19	20	7	450,920
	Buckley, Alan	2	2	46	1	13	13	20	384,137
	Buckley, Alan	3	2	12	0.561	3	4	5	422,289
	Laws, Brian	3	2	27	0.587	10	10	7	422,289
	Laws, Brian	4	2	46	1	14	18	14	426,285
	Laws, Brian	5	2	16	0.348	3	9	4	383,539
	Swain, Kenny	5	2	22	0.478	6	10	6	383,539
	Buckley, Alan	6	3	46	1	19	12	15	143,389
Halifax Town	McGrath, John	1	4	18	0.429	5	9	4	39,711
	Rathbone, Mick	1	4	24	0.571	4	15	5	39,711
Hartlepool United	Murray, Alan	1	3	28	0.609	10	10	8	68,020
	Busby, Viv	1	3	18	0.391	4	10	4	68,020
	Busby, Viv	2	3	17	0.370	4	9	4	61,366
	MacPhail, John	2	3	29	0.630	5	19	5	61,366
	McCreery, Dave	3	4	28	0.667	7	13	8	41,186
	Houchen, Keith	4	4	46	1	12	21	13	40,316
	Houchen, Keith	5	4	17	0.370	4	10	3	39,568
	Tait, Mick	5	4	24	0.522	7	12	5	39,568

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Hartlepool (cont.)	Tait, Mick	6	4	46	1	12	11	23	43,597
Hereford United	Downs, Greg	1	4	42	1	10	17	15	35,317
	Downs, Greg	2	4	42	1	12	24	6	41,660
	Layton, John	3	4	35	0.833	11	13	11	37,335
	Turner, Graham	4	4	45	0.978	19	12	14	36,645
	Turner, Graham	5	4	46	1	11	21	14	35,687
Huddersfield Town	Ross, Ian	1	3	46	1	17	20	9	95,880
	Warnock, Neil	2	3	46	1	17	15	14	76,890
	Warnock, Neil	3	3	46	1	22	9	15	102,543
	Horton, Brian	4	2	46	1	17	17	12	296,329
	Horton, Brian	5	2	46	1	13	18	15	455,966
	Jackson, Peter	6	2	37	0.804	14	16	7	437,553
Hull City	Dolan, Terry	1	3	46	1	13	22	11	78,101
	Dolan, Terry	2	3	46	1	18	14	14	86,995
	Dolan, Terry	3	3	46	1	21	14	11	80,841
	Dolan, Terry	4	3	46	1	5	25	16	73,589
	Dolan, Terry	5	4	46	1	13	15	18	45,349
	Hateley, Mark	6	4	46	1	11	27	8	33,422
Ipswich Town	McGiven, Mick	1	1	42	1	12	14	16	1,161,521
	McGiven, Mick	2	1	42	1	9	17	16	1,485,782
	Lyall, John	3	1	17	0.405	3	12	2	1,363,389
	Burley, George	3	1	22	0.524	4	16	2	1,363,389
	Burley, George	4	2	46	1	19	15	12	449,322
	Burley, George	5	2	46	1	20	12	14	301,491
	Burley, George	6	2	46	1	23	9	14	397,285
Leeds United	Wilkinson, Howard	1	1	42	1	12	15	15	2,376,240
	Wilkinson, Howard	2	1	42	1	18	8	16	2,517,879
	Wilkinson, Howard	3	1	42	1	20	9	13	2,119,454
	Wilkinson, Howard	4	1	38	1	12	19	7	1,702,768
	Graham, George	5	1	33	0.868	9	12	12	1,584,061
	Graham, George	6	1	38	1	17	13	8	2,126,698
Leicester City	Little, Brian	1	2	46	1	22	14	10	424,834
	Little, Brian	2	2	46	1	19	11	16	384,335
	Little, Brian	3	1	14	0.333	2	9	3	1,400,020
	McGhee, Mark	3	1	24	0.571	3	14	7	1,400,020
	McGhee, Mark	4	2	20	0.435	9	5	6	562,828
	O'Neill, Martin	4	2	24	0.522	9	7	8	562,828
	O'Neill, Martin	5	1	38	1	12	15	11	1,191,834
	O'Neill, Martin	6	1	38	1	13	11	14	1,687,772
Leyton Orient	Eustace, Peter	1	3	46	1	21	16	9	89,738
	Eustace, Peter	2	3	41	0.891	13	15	13	86,819
	Turner, Chris	3	3	43	0.935	6	29	8	62,582
	Holland, Pat	4	4	46	1	12	23	11	39,009
	Holland, Pat	5	4	13	0.283	4	4	5	40,632
	Taylor, Tommy	5	4	29	0.630	10	12	7	40,632
	Taylor, Tommy	6	4	46	1	19	15	12	44,529
Lincoln City	Thompson, Steve	1	4	42	1	18	15	9	42,083
	Alexander, Keith	2	4	42	1	12	19	11	56,090
	Ellis, Sam	3	4	42	1	15	16	11	39,669
	Beck, John	4	4	34	0.739	12	11	11	45,499
	Beck, John	5	4	46	1	18	16	12	44,120
	Beck, John	6	4	35	0.761	14	8	13	41,141
Liverpool	Souness, Graeme	1	1	42	1	16	15	11	1,868,494
	Souness, Graeme	2	1	26	0.619	12	7	7	1,983,708
	Evans, Roy	2	1	16	0.381	5	9	2	1,983,708
	Evans, Roy	3	1	42	1	21	10	11	2,307,686

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Liverpool (cont.)	Evans, Roy	4	1	38	1	20	7	11	3,062,969
	Evans, Roy	5	1	38	1	19	8	11	3,220,182
	Evans, Roy	6	1	38	1	18	9	11	2,822,384
Luton Town	Pleat, David	1	2	46	1	10	15	21	481,430
	Pleat, David	2	2	46	1	14	21	11	375,236
	Pleat, David	3	2	46	1	15	18	13	356,595
	Westley, Terry	4	2	21	0.457	4	11	6	395,696
	Lawrence, Lennie	4	2	24	0.522	7	11	6	395,696
	Lawrence, Lennie	5	3	46	1	21	10	15	117,609
	Lawrence, Lennie	6	3	46	1	14	17	15	99,872
Macclesfield Town	McIlroy, Sammy	6	4	46	1	23	10	13	43,716
Manchester City	Reid, Peter	1	1	42	1	15	15	12	2,034,288
	Horton, Brian	2	1	38	0.667	9	12	17	2,054,693
	Horton, Brian	3	1	42	1	12	17	13	1,762,693
	Ball, Alan	4	1	38	1	9	18	11	1,809,706
	Clark, Frank	5	2	21	0.457	9	4	8	595,584
	Clark, Frank	6	2	32	0.696	7	16	9	536,431
	Royle, Joe	6	2	14	0.304	5	6	3	536,431
Manchester United	Ferguson, Alex	1	1	42	1	24	6	12	2,136,011
	Ferguson, Alex	2	1	42	1	27	4	11	2,533,539
	Ferguson, Alex	3	1	42	1	26	6	10	2,657,646
	Ferguson, Alex	4	1	38	1	25	6	7	2,565,629
	Ferguson, Alex	5	1	38	1	21	5	12	2,944,093
	Ferguson, Alex	6	1	38	1	23	7	8	2,882,346
Mansfield Town	Foster, George	1	3	46	1	11	24	11	70,887
	King, Andy	2	4	27	0.643	9	12	6	57,697
	King, Andy	3	4	42	1	18	13	11	58,143
	King, Andy	4	4	46	1	11	15	20	44,775
	Parkin, Steve	5	4	34	0.739	14	11	9	39,548
	Parkin, Steve	6	4	46	1	16	13	17	44,053
Middlesbrough	Lawrence, Lennie	1	1	42	1	11	20	11	1,448,268
	Lawrence, Lennie	2	2	45	0.978	17	15	13	635,415
	Robson, Bryan	3	2	46	1	23	10	13	457,322
	Robson, Bryan	4	1	38	1	11	17	10	1,562,931
	Robson, Bryan	5	1	38	1	10	16	12	2,182,744
	Robson, Bryan	6	2	46	1	27	9	10	558,954
Millwall	McCarthy, Mick	1	2	46	1	18	12	16	430,881
	McCarthy, Mick	2	2	46	1	19	10	17	333,577
	McCarthy, Mick	3	2	46	1	16	16	14	338,363
	McCarthy, Mick	4	2	29	0.630	10	9	10	406,816
	Nicholl, Jimmy	4	2	17	0.370	3	11	3	406,816
	Nicholl, Jimmy	5	3	30	0.652	12	10	8	102,574
	Docherty, John	5	3	16	0.348	4	7	5	102,574
	Bonds, Billy	6	3	46	1	14	19	13	115,742
Newcastle United	Keegan, Kevin	1	2	46	1	29	8	9	555,442
	Keegan, Kevin	2	1	42	1	23	11	8	1,568,161
	Keegan, Kevin	3	1	42	1	20	10	12	2,285,813
	Keegan, Kevin	4	1	38	1	24	8	6	2,187,772
	Keegan, Kevin	5	1	21	0.553	11	6	4	2,431,655
	Dalglish, Kenny	5	1	16	0.421	8	2	6	2,431,655
	Dalglish, Kenny	6	1	38	1	11	16	11	2,364,466
Northampton Town	Chard, Phil	1	4	42	1	11	23	8	32,050
	Barnwell, John	2	4	36	0.783	9	18	9	45,994
	Barnwell, John	3	4	21	0.5	3	9	9	43,958
	Atkins, Ian	3	4	19	0.452	7	7	5	43,958
	Atkins, Ian	4	4	46	1	18	15	13	37,133

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Northampton (cont.)	Atkins, Ian	5	4	46	1	20	14	12	45,477
	Atkins, Ian	6	3	46	1	18	11	17	81,657
Norwich City	Walker, Mike	1	1	42	1	21	12	9	1,702,615
	Walker, Mike	2	1	23	0.548	10	6	7	1,905,018
	Deehan, John	2	1	19	0.452	2	7	10	1,905,018
	Deehan, John	3	1	38	0.9048	10	16	12	1754520
	O'Neill, Martin	4	2	22	0.478	9	6	7	605,697
	Megson, Gary	4	2	24	0.522	5	11	8	605,697
	Walker, Mike	5	2	46	1	17	17	12	430,119
	Walker, Mike	6	2	45	0.978	13	19	13	371,748
Nottingham Forest	Clough, Brian	1	1	41	0.976	10	21	10	2,212,353
	Clark, Frank	2	2	46	1	23	9	14	705,141
	Clark, Frank	3	1	42	1	22	9	11	1,546,331
	Clark, Frank	4	1	38	1	15	10	13	2,165,794
	Clark, Frank	5	1	17	0.447	1	9	7	2,112,653
	Bassett, Dave	5	1	12	0.316	1	4	7	2,112,653
	Bassett, Dave	6	2	46	1	28	8	10	664,862
Notts County	Warnock, Neil	1	2	24	0.522	4	12	8	478,882
	Walker, Mick	1	2	22	0.478	8	6	8	478,882
	Walker, Mick	2	2	46	1	20	18	8	412,965
	Slade, Russell	3	2	18	0.391	3	11	4	387,086
	Kendall, Howard	3	2	16	0.348	4	7	5	387,086
	Thompson, Steve	4	3	46	1	21	10	15	92,804
	Thompson, Steve	5	3	23	0.5	5	12	6	85,674
	Allardyce, Sam	5	3	21	0.457	2	13	6	85,674
	Allardyce, Sam	6	4	46	1	29	5	12	62,778
Oldham Athletic	Royle, Joe	1	1	42	1	13	19	10	1,831,158
	Royle, Joe	2	1	42	1	9	20	13	1,774,512
	Royle, Joe	3	2	16	0.348	5	7	4	580,509
	Sharp, Graeme	3	2	29	0.630	11	10	8	580,509
	Sharp, Graeme	4	2	46	1	14	18	14	375,139
	Sharp, Graeme	5	2	29	0.630	6	13	10	378,900
	Warnock, Neil	5	2	17	0.367	4	10	3	378,900
	Warnock, Neil	6	3	46	1	15	15	16	110,503
Oxford United	Horton, Brian	1	2	46	1	14	18	14	510,136
	Smith, Denis	2	2	41	0.891	11	20	10	413,893
	Smith, Denis	3	3	46	1	21	13	12	123,827
	Smith, Denis	4	3	46	1	24	11	11	101,521
	Smith, Denis	5	2	46	1	16	21	9	280,069
	Smith, Denis	6	2	23	0.5	7	11	5	409,225
	Shotton, Malcolm	6	2	19	0.413	9	6	4	409,225
Peterborough United	Turner, Chris	1	2	18	0.391	7	5	6	306,295
	Fuccillo, Lil	1	2	28	0.609	9	11	8	306,295
	Fuccillo, Lil	2	2	22	0.478	3	11	8	376,126
	Still, John	3	3	46	1	14	14	18	98,882
	Still, John	4	3	13	0.283	3	5	5	94,474
	Halsall, Mick	4	3	33	0.717	10	15	8	94,474
	Fry, Barry	5	3	46	1	11	21	14	99,867
	Fry, Barry	6	4	46	1	18	15	13	50,856
Plymouth Argyle	Shilton, Peter	1	3	46	1	16	18	12	117,433
	Shilton, Peter	2	3	46	1	25	11	10	94,310
	Shilton, Peter	3	3	22	0.478	6	13	3	103,454
	McCall, Steve	3	3	15	0.326	3	9	3	103,454
	Warnock, Neil	4	4	46	1	22	12	12	53,924
	Warnock, Neil	5	3	29	0.630	7	11	11	766,227
	Jones, Mick	6	3	46	1	12	21	13	92,116

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Portsmouth	Smith, Jim	1	2	46	1	26	10	10	475,327
	Smith, Jim	2	2	46	1	15	18	13	465,552
	Smith, Jim	3	2	28	0.609	7	12	9	437,163
	Fenwick, Terry	3	2	18	0.391	8	6	4	437,163
	Fenwick, Terry	4	2	46	1	13	20	13	367,552
	Fenwick, Terry	5	2	46	1	20	18	8	411,737
	Fenwick, Terry	6	2	25	0.544	6	14	5	383,294
	Ball, Alan	6	2	20	0.435	7	8	5	383,294
Port Vale	Rudge, John	1	3	46	1	26	9	11	128,889
	Rudge, John	2	3	46	1	26	10	10	90,156
	Rudge, John	3	2	46	1	15	18	13	325,309
	Rudge, John	4	2	46	1	15	16	15	420,519
	Rudge, John	5	2	46	1	17	13	16	364,450
	Rudge, John	6	2	46	1	13	23	10	354,591
Preston North End	Beck, John	1	3	28	0.609	7	17	4	84,988
	Beck, John	2	4	42	1	18	11	13	58,727
	Beck, John	3	4	17	0.405	6	9	2	47,050
	Peters, Gary	3	4	25	0.595	13	4	8	47,050
	Peters, Gary	4	4	46	1	23	6	17	48,192
	Peters, Gary	5	3	46	1	18	21	7	96,208
	Peters, Gary	6	3	26	0.565	9	12	5	110,679
	Moyes, David	6	3	20	0.435	6	5	9	110,679
Queens Park Rangers	Francis, Gerry	1	1	42	1	17	13	12	1,781,428
	Francis, Gerry	2	1	42	1	16	14	12	1,678,575
	Francis, Gerry	3	1	14	0.333	3	7	4	1,563,964
	Wilkins, Ray	3	1	28	0.667	14	9	5	1,563,964
	Wilkins, Ray	4	1	38	1	9	23	6	1,447,933
	Houston, Stewart	5	2	40	0.870	16	14	10	559,498
	Houston, Stewart	6	2	16	0.348	6	6	4	536,249
	Harford, Ray	6	2	26	0.565	3	10	13	536,249
Reading	McGhee, Mark	1	3	46	1	18	13	15	77,563
	McGhee, Mark	2	3	46	1	26	9	11	82,239
	McGhee, Mark	3	2	21	0.457	9	6	6	272,025
	Quinn, Jimmy	3	2	25	0.544	14	7	4	272,025
	Quinn, Jimmy	4	2	46	1	13	16	17	342,662
	Quinn, Jimmy	5	2	46	1	15	19	12	318,112
	Bullivant, Terry	6	2	38	0.826	10	19	9	386,983
Rochdale	Sutton, Dave	1	4	42	1	16	16	10	40,377
	Sutton, Dave	2	4	42	1	16	14	12	43,546
	Sutton, Dave	3	4	17	0.405	6	8	3	38,668
	Docherty, Mick	3	4	19	0.452	4	5	10	38,668
	Docherty, Mick	4	4	46	1	14	19	13	31,099
	Barrow, Graham	5	4	46	1	14	16	16	36,148
	Barrow, Graham	6	4	46	1	17	22	7	37,179
Rotherham United	Henson, Phil	1	3	46	1	17	15	14	80,164
	Henson, Phil	2	3	46	1	15	18	13	79,424
	Gemmill, Archie	3	3	39	0.848	13	13	13	77,707
	Gemmill, Archie	4	3	46	1	14	18	14	95,776
	Bergera, Danny	5	3	36	0.783	6	19	11	79,320
	Moore, Ronnie	6	4	46	1	16	11	19	51,428
Scarborough	McHale, Ray	1	4	37	0.881	14	15	8	40,410
	Chambers, Phil	2	4	11	0.262	3	6	2	35,111
	Wicks, Steve	2	4	30	0.714	12	12	6	35,111
	Ayre, Billy	3	4	17	0.405	2	11	4	42,739
	McHale, Ray	3	4	12	0.286	2	6	4	42,739
	McHale, Ray	4	4	35	0.761	7	13	15	33,526

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Scarborough (cont.)	Wadsworth, Mick	5	4	46	1	16	15	15	34,320
	Wadsworth, Mick	6	4	46	1	19	12	15	40,206
Scunthorpe United	Green, Bill	1	4	20	0.476	7	8	5	47,384
	Money, Richard	1	4	22	0.524	7	8	7	47,384
	Money, Richard	2	4	31	0.738	9	11	11	47,401
	Moore, David	3	4	42	1	18	16	8	45,128
	Moore, David	4	4	33	0.717	9	14	10	47,346
	Buxton, Mick	4	4	13	0.283	6	2	5	47,346
	Buxton, Mick	5	4	29	0.630	11	13	5	39,935
	Laws, Brian	5	4	17	0.370	7	6	4	39,935
	Laws, Brian	6	4	46	1	19	15	12	41,116
Sheffield United	Bassett, Dave	1	1	42	1	14	18	10	1,672,182
	Bassett, Dave	2	1	42	1	8	16	18	1,384,463
	Bassett, Dave	3	2	46	1	17	12	17	620,438
	Bassett, Dave	4	2	21	0.457	5	13	3	512,858
	Kendall, Howard	4	2	25	0.544	11	3	11	512,858
	Kendall, Howard	5	2	46	1	20	13	13	602,259
	Spackman, Nigel	6	2	34	0.739	15	6	13	516,749
Sheffield Wednesday	Francis, Trevor	1	1	42	1	15	13	14	2,015,421
	Francis, Trevor	2	1	42	1	16	10	16	1,641,871
	Francis, Trevor	3	1	42	1	13	17	12	1,891,375
	Pleat, David	4	1	38	1	10	18	10	1,487,579
	Pleat, David	5	1	38	1	14	9	15	2,036,642
	Pleat, David	6	1	13	0.342	2	8	3	2,254,576
	Atkinson, Ron	6	1	24	0.632	9	10	5	2,254,576
Shrewsbury Town	Bond, John	1	4	42	1	17	14	11	53,474
	Davies, Fred	2	4	42	1	22	7	13	34,736
	Davies, Fred	3	3	46	1	13	19	14	52,712
	Davies, Fred	4	3	46	1	13	19	14	76,513
	Davies, Fred	5	3	46	1	11	22	13	75,896
	King, Jake	6	4	46	1	16	17	13	44,479
Southampton	Branfoot, Ian	1	1	42	1	13	18	11	1,552,123
	Branfoot, Ian	2	1	24	0.571	5	16	3	1,648,611
	Ball, Alan	2	1	17	0.405	6	7	4	1,648,611
	Ball, Alan	3	1	42	1	12	12	18	1,999,025
	Merrington, Dave	4	1	38	1	9	18	11	1,988,071
	Souness, Graeme	5	1	38	1	10	17	11	2,089,849
	Jones, Dave	6	1	38	1	14	18	6	1,706,571
Southend United	Murphy, Colin	1	2	37	0.804	8	17	12	508,123
	Fry, Barry	2	2	19	0.413	10	5	4	383,489
	Taylor, Peter	2	2	26	0.565	7	15	4	383,489
	Taylor, Peter	3	2	32	0.696	10	16	6	431,037
	Thompson, Steve	3	2	14	0.304	8	4	2	431,037
	Whelan, Ronnie	4	2	46	1	15	17	14	416,690
	Whelan, Ronnie	5	2	46	1	8	23	15	369,018
	Martin, Alvin	6	3	46	1	11	25	10	104,983
Stockport County	Bergera, Danny	1	3	46	1	19	12	15	95,739
	Bergera, Danny	2	3	46	1	24	9	13	105,568
	Bergera, Danny	3	3	39	0.848	16	17	6	99,254
	Jones, Dave	4	3	46	1	19	14	13	92,581
	Jones, Dave	5	3	46	1	23	10	13	88,263
	Megson, Gary	6	2	46	1	19	19	8	330,869
Stoke City	Macari, Lou	1	3	46	1	27	7	12	111,686
	Jordan, Joe	2	2	31	0.674	11	10	10	357,984
	Macari, Lou	2	2	12	0.261	4	5	3	357,984
	Macari, Lou	3	2	37	0.804	12	11	14	358,174

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Stoke (cont.)	Macari, Lou	4	2	46	1	20	13	13	402,323
	Macari, Lou	5	2	46	1	18	18	10	336,769
	Bates, Chic	6	2	27	0.587	8	11	8	392,808
	Kamara, Chris	6	2	14	0.304	1	8	5	392,808
Sunderland	Crosby, Malcolm	1	2	25	0.544	8	11	6	441,077
	Butcher, Terry	1	2	21	0.457	5	11	5	441,077
	Butcher, Terry	2	2	17	0.370	5	10	2	497,968
	Buxton, Mick	2	2	29	0.630	14	9	6	497,968
	Buxton, Mick	3	2	39	0.848	9	15	15	503,260
	Reid, Peter	4	2	46	1	22	7	17	408,704
	Reid, Peter	5	1	38	1	10	18	10	1,118,495
	Reid, Peter	6	2	46	1	26	8	12	648,153
Swansea City	Burrows, Frank	1	3	46	1	20	13	13	90,631
	Burrows, Frank	2	3	46	1	16	18	12	101,365
	Burrows, Frank	3	3	46	1	19	13	14	111,642
	Burrows, Frank	4	3	12	0.261	3	4	5	97,148
	Molby, Jan	4	3	15	0.326	6	5	4	97,148
	Molby, Jan	5	4	46	1	21	17	8	55,378
	Molby, Jan	6	4	10	0.217	3	6	1	49,424
	Cork, Alan	6	4	33	0.717	10	13	10	49,424
Swindon Town	Hoddle, Glenn	1	2	46	1	21	12	13	393,342
	Gorman, John	2	1	42	1	5	22	15	1,351,343
	Gorman, John	3	2	17	0.370	6	8	3	565,839
	McMahon, Steve	3	2	27	0.587	6	13	8	565,839
	McMahon, Steve	4	3	46	1	25	4	17	145,291
	McMahon, Steve	5	2	46	1	15	22	9	284,573
	McMahon, Steve	6	2	46	1	14	22	10	405,059
Torquay United	Compton, Paul	1	4	32	0.696	9	20	3	40,727
	O'Riordan, Don	1	4	10	0.217	3	3	4	40,727
	O'Riordan, Don	2	4	42	1	17	9	16	36,854
	O'Riordan, Don	3	4	42	1	14	15	13	35,727
	O'Riordan, Don	4	4	14	0.304	2	8	4	33,946
	May, Eddie	4	4	30	0.652	3	17	10	33,946
	Hodges, Kevin	5	4	46	1	13	22	11	36,886
	Hodges, Kevin	6	4	46	1	21	14	11	27,308
Tottenham Hotspur	Livermore, Doug	1	1	42	1	16	15	11	1,758,886
	Ardiles, Ossie	2	1	42	1	11	19	12	1,717,602
	Ardiles, Ossie	3	1	12	0.286	5	5	2	1,771,781
	Francis, Gerry	3	1	29	0.691	11	6	12	1,771,781
	Francis, Gerry	4	1	38	1	16	9	13	2,099,836
	Francis, Gerry	5	1	38	1	13	18	7	2,069,147
	Francis, Gerry	6	1	14	0.368	3	7	4	1,997,091
	Gross, Christen	6	1	24	0.632	8	9	7	1,997,091
Tranmere Rovers	King, John	1	2	46	1	23	13	10	441,552
	King, John	2	2	46	1	21	16	9	365,473
	King, John	3	2	46	1	22	14	10	367,075
	King, John	4	2	40	0.870	12	15	13	346,262
	Aldridge, John	5	2	46	1	17	15	14	342,281
	Aldridge, John	6	2	46	1	14	18	14	355,315
Walsall	Hibbitt, Kenny	1	4	42	1	22	13	7	35,870
	Hibbitt, Kenny	2	4	42	1	17	16	9	48,916
	Nicholl, Chris	3	4	35	0.833	23	5	7	44,482
	Nicholl, Chris	4	3	46	1	19	15	12	65,157
	Nicholl, Chris	5	3	46	1	19	17	10	71,918
Watford	Perryman, Steve	1	2	46	1	14	19	13	541,061
	Roeder, Glenn	2	2	46	1	15	22	9	421,235

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
Watford (cont.)	Roeder, Glenn	3	2	46	1	19	14	13	478,412
	Roeder, Glenn	4	2	28	0.609	5	13	10	485,297
	Jackett, Kenny	5	3	46	1	16	11	19	130,579
	Taylor, Graham	6	3	46	1	24	6	16	97,395
West Bromwich Albion	Ardiles, Ossie	1	3	46	1	25	11	10	84,892
	Burkinshaw, Keith	2	2	46	1	13	21	12	378,849
	Burkinshaw, Keith	3	2	11	0.239	1	6	4	439,290
	Buckley, Alan	3	2	34	0.739	14	14	6	439,290
	Buckley, Alan	4	2	46	1	16	18	12	508,283
	Buckley, Alan	5	2	27	0.587	7	8	12	488,404
	Harford, Ray	5	2	15	0.326	6	8	1	488,404
	Harford, Ray	6	2	20	0.435	11	5	4	458,836
	Smith, Denis	6	2	23	0.5	4	10	9	458,836
West Ham United	Bonds, Billy	1	2	46	1	26	10	10	576,790
	Bonds, Billy	2	1	42	1	13	16	13	1,114,139
	Redknapp, Harry	3	1	42	1	13	18	11	1,753,559
	Redknapp, Harry	4	1	38	1	14	15	9	1,765,628
	Redknapp, Harry	5	1	38	1	10	16	12	1,774,759
	Redknapp, Harry	6	1	38	1	16	14	8	2,107,070
Wigan Athletic	Hamilton, Brian	1	3	34	0.739	8	16	10	94,683
	Philpotts, Dave	1	3	12	0.261	2	9	1	94,683
	Swain, Kenny	2	4	42	1	11	19	12	36,479
	Barrow, Graham	3	4	35	0.833	13	12	10	40,342
	Barrow, Graham	4	4	11	0.239	3	4	4	41,659
	Deehan, John	4	4	30	0.652	15	11	4	41,659
	Deehan, John	5	4	46	1	26	11	9	42,361
	Deehan, John	6	3	46	1	17	18	11	91,313
Wimbledon	Kinnear, Joe	1	1	42	1	14	16	12	1,820,400
	Kinnear, Joe	2	1	42	1	18	13	11	1,833,717
	Kinnear, Joe	3	1	42	1	15	16	11	1,689,519
	Kinnear, Joe	4	1	38	1	10	17	11	1,676,089
	Kinnear, Joe	5	1	38	1	15	12	11	1,702,040
	Kinnear, Joe	6	1	38	1	10	14	14	1,802,362
Wolves[a]	Turner, Graham	1	2	46	1	16	17	13	492,165
	Turner, Graham	2	2	33	0.717	11	9	13	526,259
	Taylor, Graham	2	2	11	0.239	5	3	3	526,259
	Taylor, Graham	3	2	46	1	21	12	13	455,666
	Taylor, Graham	4	2	16	0.348	4	6	6	433,013
	McGhee, Mark	4	2	25	0.544	8	8	9	433,013
	McGhee, Mark	5	2	46	1	22	14	10	451,335
	McGhee, Mark	6	2	46	1	18	17	11	470,836
Wrexham	Flynn, Brian	1	4	42	1	23	8	11	46,561
	Flynn, Brian	2	3	46	1	17	18	11	69,402
	Flynn, Brian	3	3	46	1	16	15	15	85,700
	Flynn, Brian	4	3	46	1	18	12	16	105,983
	Flynn, Brian	5	3	46	1	17	11	18	94,301
	Flynn, Brian	6	3	46	1	18	12	16	88,751
Wycombe Wanderers	O'Neill, Martin	2	4	42	1	19	10	13	28,358
	O'Neill, Martin	3	3	46	1	21	10	15	66,630
	Smith, Alan	4	3	46	1	15	16	15	83,512
	Gregory, John	5	3	34	0.739	13	15	6	86,885
	Gregory, John	6	3	33	0.717	9	11	13	87,779
	Smillie, Neil	6	3	12	0.261	5	2	5	87,779
York City	Ward, John	1	4	32	0.762	15	6	11	41,587
	Little, Alan	1	4	10	0.238	6	3	1	41,587
	Little, Alan	2	3	46	1	21	13	12	72,088

Club Name	Manager Name	Time Period	Division	Matches	Weighting	Wins	Losses	Draws	Valuation (£)
York (cont.)	Little, Alan	3	3	46	1	21	16	9	96,470
	Little, Alan	4	3	46	1	13	20	13	104,749
	Little, Alan	5	3	46	1	13	20	13	79,990
	Little, Alan	6	3	46	1	14	15	17	89,413

Notes: managers for each club listed in chronological order. Time period 1 refers to football season 1992/93, time period 2 refers to football season 1993/94 and so on.
Divisions 1-4 based on old classification (i.e., prior to Premier League). Division 1 refers to the Premier League; Division 2 refers to Football League Division 1; Division 3 refers to Football League Division 2; and Division 4 refers to Football League Division 3.
[a] Abbreviated name. Full name = Wolverhampton Wanderers.

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