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EXPLAINING THE GROWTH IN THE NUMBER OF APPLICATIONS TO INDUSTRIAL TRIBUNALS, 1972-1997

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The views expressed in this report are the authors' and do not necessarily reflect those of the Department of Trade and Industry.

Foreword

Promoting good employment relations is an important task of government. Our role in the Department of Trade and Industry is to encourage the development of a skilled and flexible labour market founded on the principle of partnership at work.

The Department commissions an ongoing programme of evaluation and research in employment relations. In-house researchers, economists and policy advisors devise research projects to be conducted on our behalf by external researchers, who are chosen through a competitive tendering process. Projects typically look at areas where we are interested in identifying good practice, in assessing the impact of particular policies or regulations, or examining emergent trends. Details of the programme appear regularly in *Labour Market Trends* and can be found at **http:/www.dti.gov.uk/er/emar**

The Research Series is where we disseminate the results of this work. The views expressed in these publications do not necessarily reflect that of the Department. We publish these reports as a contribution towards an open debate about how we might best achieve our overall aim of improving competitiveness.

Mark Beatson
Director, Employment Market Analysis and Research Branch

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Executive Summary

Background

This study was commissioned by the Department of Trade and Industry to explain the increase in applications to Industrial Tribunals. At 89,000 the number of applications in 1996/97 was more than twice the number in 1985. Part of this can be attributed to the introduction of new rights but there was also an increase in the number of claims for individual jurisdictions. However they grew in different ways. The numbers of discrimination cases rose more or less continuously as did the number of Wages Act cases, whereas Unfair dismissals rose dramatically in 1991/2 and the residual category shows no growth.

The report advances an economic explanation of these patterns. We approach the problem in two stages. First, we set out an economic framework or model, identifying potential explanatory variables. Second, we collect data on the explanatory variables and carry out an econometric analysis to see if we can identify a statistical relationship between these variables and what we wish to explain.

An economic model

In our framework to analyse the behaviour giving rise to applications to Industrial Tribunals we conceptually split the process into two parts:

- the number of potentially actionable events that arise, and
- the chance of such an event triggering an application.

We argue that the former is generated as the outcome of the interaction between employers and workers in the workplace, with firms balancing the gains from management rule with the costs of potential litigation. The state of product market competition and labour markets will also influence the incentive for managers to behave reasonably. This suggests that the explanatory factors influencing this trade-off might be:

- the presence of unions;
- employment in small firms;
- the industrial structure of the economy;
- demographic structure of the workforce; and
- the state of the economy.

Turning to the likelihood of an application being made following a trigger event, we model this as a cost-benefit decision by the worker. If she or he views the expected gain from making an application as outweighing the monetary and non-monetary costs of going through the legal procedure, then an application will be lodged. This suggests as explanatory factors:

- the expected chance of winning a case;
- the expected payment;
- perceptions of the support available through the process; and
- the prospects of finding an alternative job.

Method

For analysis, the total number of applications is divided into broad categories:

- unfair dismissal,
- sex and race discrimination,
- Wages Act (with breach of contract)
- redundancy and insolvency, and
- all “other” cases.

Each of these is modelled separately, as we would expect the explanatory variables to have a different significance for the different types of employment rights.

We analyse three sets of data. First, and most important, national data from the Employment Tribunal Service for the period 1985 to 1997. We could not get earlier data and data on outcomes in the last years is unavailable. This means we have only 11 observations which limits the scope for statistical analysis. To augment this national data we examine two other sources of data:

- disaggregated data for the same period by region from ACAS, which we use in an attempt to enhance the reliability of our findings;
- a longer series of data, back to 1972, on unfair dismissals only, which allows us to check the robustness of our results over a more extended period.

We investigate these three datasets using a combination of graphical and statistical techniques, appropriate to the length of data series, including simple regression analysis.

Results

It is necessary to stress the limitations imposed on the analyses by the data available, and we have adjusted our method accordingly where possible.

The statistical analysis generally supports the economic model: in other words the economic variables appear to be important in explaining the number of applications.

The expected value of bringing a case appears to play a substantial role in explaining the rise in the number of applications. The probability of

winning a case (lagged) is significantly associated with the number of unfair dismissal cases, the number of Wages Act cases and the number of redundancy cases. The amount of money awarded in discrimination cases is significantly associated with the number of discrimination cases.

Furthermore, associations are found between the number of cases and the industrial structure and labour force composition. The associations have economic meaning. Thus:

- the rise in the number of discrimination cases is closely linked to the rise in the number of women in the labour force;
- the number of unfair dismissal cases is related to the number employed in small enterprises where lack of formal structures are such that legislative redress is more often used in the case of a dispute;
- the rise in redundancy cases is closely associated with the decline in manufacturing employment;
- the decline in union membership and the associated power of the unions, which may reflect a move towards more adversarial workplace employment relations, is also associated with the rise in several jurisdictions, particularly Wages Act cases.

Movements in these economic variables can therefore help explain the changes in the number of applications over this period. We find that the level of unemployment, used as an indicator of the state of the economy, is not a significant factor.

Analysis of regional data for the same period enables us to make use of more observations, which means that we can see whether the model can be improved by the addition of another independent variable. Examination of the results shows that adding extra variables does not substantially improve the equations. The analysis of the longer-term series for unfair dismissal cases indicates that the relationship with success rates is robust over a longer period.

Limitations to the data available mean that our results must remain tentative. Nevertheless, we believe that they do form a reasonable basis for: (a) understanding the substantial changes in the number of ET applications, and (b) short range forecasting.

Forecasting

We conclude by listing our preferred equations for use in short-term forecasting. In these equations:

- the number of unfair dismissal cases is related to the past probability of winning a case (under this jurisdiction) and to the proportion of employees in small workplaces;
- the number of discrimination cases is closely related to the proportion of employees who are female;
- the number of Wages Act cases is related to the past probability of winning a case (under this jurisdiction) and to trade union membership, (a fall in trade union membership leading to an increase in tribunal cases);
- the number of redundancy cases is related to variations in the past probability of winning a case (under this jurisdiction) and the proportion of employees who are in manufacturing, (so a decline in manufacturing employment is associated with an increase in the number of redundancy cases).

A forecasting model for total applications is derived from these estimates for each jurisdiction. This forecasting model explains 83 percent of the variation in total applications over the period covered by the data.

One
INTRODUCTION

1.1 Background

The purpose of this study is to statistically investigate explanations for the increase in the number of applications to Industrial Tribunals (IT). Industrial Tribunals came into being in 1964, were extended into individual rights following the Redundancy Payments Act of 1965, and received a major extension with the introduction of protection against unfair dismissals in the Industrial Relations Act of 1971. The number of applications grew slowly during the seventies. The responsibilities of ITs widened with the introduction of anti-discrimination legislation. By the 1980s they were an established part of the industrial relations environment, and the extension of individual employment rights in the 1980s meant they were given additional areas of responsibility. Their purpose is to provide speedy and accessible remedies that avoid the legalism of the courts. The 1998 Employment Rights (Dispute Resolution) Act led to the name being changed to Employment Tribunals, but in this report we shall use IT as the standard abbreviation.

The number of claims in the 1980s appeared to move with the economic cycle, but after a rise in the 1990s recession, the subsequent recovery did not see a return to former levels. In 1996 the total number of IT applications was 88,918 which was 3 per 1,000 employees. This total was more than twice the 1988 figure of 29,304: a quite dramatic increase *(Figure 1)*.

Table 1 below breaks the IT total into five broad categories. It shows that much of the increase can be explained by the introduction of new rights in the 1980s and 1990s, but also that there was an increasing number of claims within each category. The stability of unfair dismissal cases after 1991 is particularly noteworthy.

The growth in the number of applications is an issue for the Employment Tribunal Service and related bodies such as ACAS and the DTI. This remains a key issue because the increase is likely to be compounded by applications under the new rights created by the Working Time Regulations and the National Minimum Wage legislation.

1.2 Objective

The DTI commissioned this study to see whether it is possible, by using statistical analysis, to explain the increase in the number of IT cases by reference to changes in the labour market and the broader economy. An unexplained time trend is very unsatisfactory, whereas an understanding of economic factors can help with medium-term planning and in assessing the potential impact of developments.

Figure 1: Total applications

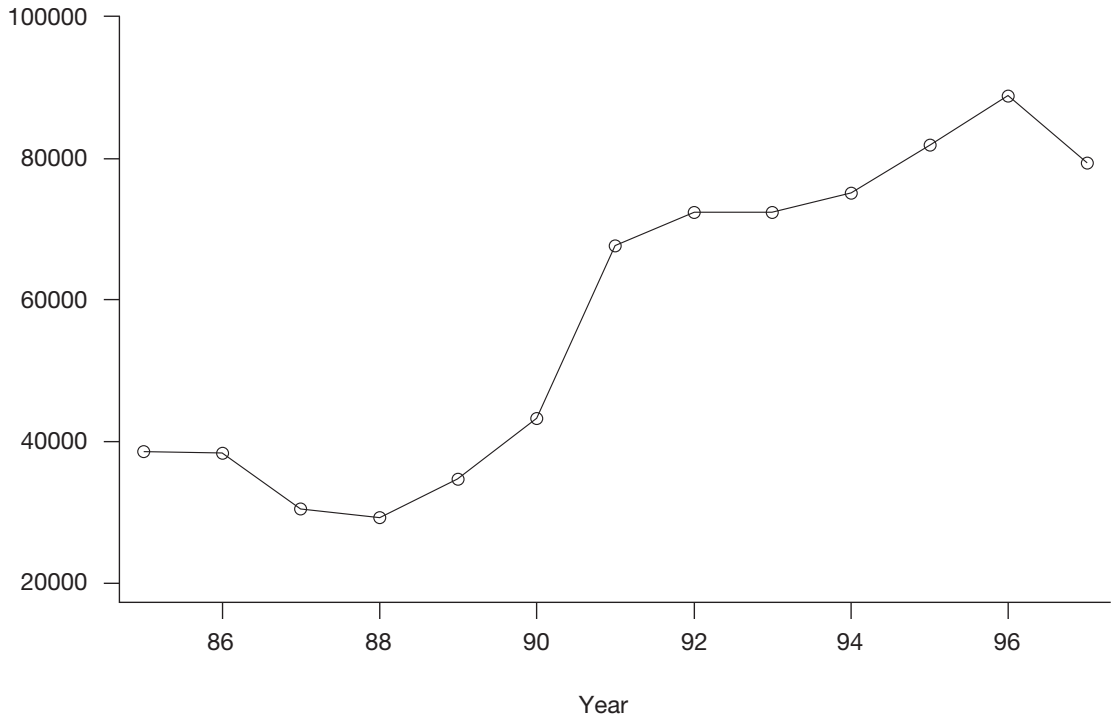


Table 1: Number of registered applications to Industrial Tribunals

Year	*Total*	*Unfair dismissal*	*Redundancy*	*Discrimination*	*Wages Act & breach of contract*	*Other*
1985	38590	28010	4592	3051	0	2937
1986	38395	24783	3502	2139	34	7937
1987	30510	19370	2876	3371	1889	3004
1988	29304	18159	2533	2593	2628	3391
1989	34703	19806	3314	3349	5416	2818
1990	43244	25813	4298	3766	6237	3130
1991	67691	40022	9041	5528	9681	3419
1992	72377	40918	9149	7298	12041	2971
1993	72346	41495	9734	5649	11244	4254
1994	75172	38597	10256	6308	14931	5080
1995	81894	40034	7984	6528	22055	5242
1996	88918	39087	6237	7779	23132	12148
1997	79372	37884	5522	8333	23419	3614

The project's terms of reference were to explain the rise in the total number of applications to ITs, with a particular focus on unfair dismissal cases as they account for over half the total. In this study we identify and quantify the effects of a range of economic and social factors and seek to provide a coherent explanation of the trend change in IT applications.

1.3 Outline of the report

We approach this problem in two stages.

- First, we set out an economic model, identifying potential explanatory variables.
- Second, we collect data on the explanatory variables and carry out an econometric analysis to identify statistical relationships between these variables and applications to ITs.

In Chapter 2 we describe the economic model. We conceptualise a two-part process:

- the number of potentially actionable events that arise; and the chance of such an event triggering an application. From this we identify potential explanatory variables.

In Chapter 3 we describe the data sources and note the limitations that the data impose on the scope for statistical analysis. In Chapter 4 we present the results of the analysis – identifying five categories of jurisdictions and using three datasets. For each category of jurisdictions we present a graphical analysis and identify correlations with economic variables. We then proceed to a multivariate analysis. This analysis allows us to identify our favoured forecasting equations.

Two
OUR APPROACH

2.1 An Economic Model

We approach the problem of explaining the trend rise in IT applications by sketching an economic model of behaviour. Workers, unions and firms are active decision-makers shaping the work environment. Workers will choose whether to pursue claims on the basis of the perceived costs and benefits of doing so. An understanding of the rise in the level of claims requires identification of these costs and benefits. From this follows a classification of the data used in the study.

Claims are the outcome of both worker and firm behaviour and we deal with each in turn. We begin by looking at worker behaviour and the likelihood that a trigger event leads to a case being brought. Then, to complete the model, we consider the number of potential trigger events, and the wider role of employers and unions in shaping the work environment.

2.1.1 Behaviour of workers

For the moment, we ignore the fact that the ITs hear cases under different jurisdictions and consider a generic case brought by a worker. Some event may happen to trigger such a case – perhaps the worker is dismissed or thinks she or he has been discriminated against. The worker then has to weigh the costs and benefits of bringing a case.

The benefits are determined by the probability of winning the case and the expected outcome if the case is won. The costs are the expected costs of losing. Net expected benefits are the probability of winning the case multiplied by the expected outcome if the case is won plus the probability of losing the case multiplied by the costs of losing the case.

We assume that the likelihood that a worker will bring a case depends on three things.

- First, the net expected benefits (denoted *NXB*) describe the pure monetary return.
- Second, the individual might be influenced by the level of support (denoted S) that she or he might receive in bringing the case. Despite the relative informality of the IT system, it can still be a daunting experience. Support could come from a Citizens Advice Bureau, trade union or outside bodies such as the Equal Opportunities Commission or the Commission for Racial Equality.
- Third, the general level of litigiousness *(L)* in society at large might influence the propensity to resort to legal redress.

To summarise the argument so far, we assume that the probability of a worker bringing a case following some 'trigger' incident, which we denote π, depends on the net expected benefit of so doing, the level of support available and a general indicator of the use of legal action:

$$\pi = f(NXB, S, L) \qquad (1)$$

We now consider in more detail each component of NXB.

a) The probability of winning

A large factor in the chance of winning an application will be the merits of the individual case, but that is not something that can be known or modelled in a study such as this. We assume that the individual knows the *average* chance of winning for all cases *(p)* and assesses his or her chances on this basis.

b) The benefits of winning

A key component of the expected value of winning is the value of the award, *A*. This is usually monetary but can involve reinstatement in the case of unfair dismissal procedures. Given this, the alternative to winning might be no award and/or unemployment. The expected value of *A* for any particular case therefore will depend on the average value of awards pertaining at the time *(V)* and level of unemployment *(U)*, so:

$$A = A(V, U) \qquad (2)$$

c) The cost of losing

The direct cost of losing is likely to be small. If workers lose they do not pay costs. However, there may be non-financial costs such as stress. These are likely to be mitigated by the presence of support systems for the individual bringing a case.

This analysis suggests that the net expected benefits of winning depend on the probability of winning, the average value of the award and the level of unemployment, *NXB (p, V, U)*. We put all this together to show that the probability of a case being brought, conditional on a potential trigger event, is given by:

$$\pi = f(p, V, U, S, L) \qquad (3)$$

2.1.2 Behaviour of firms and unions

Events happen that can lead a worker to feel unfairly treated. Do these just happen randomly? The correct answer is "yes and no". Consider traffic accidents. These are not intentional and appear to happen randomly. But while people

clearly do not intend to have an accident, their method of driving does influence the *probability* of having an accident. Similarly with workplace incidents, employers (and unions) create the working environment in which potentially actionable events can take place.[1] These events we denote *N*.

While the climate or culture of a workplace is partly driven by history, managers also actively shape the working environment. One issue in recent years has been the discussion of the greater prevalence of more "aggressive" managerial styles. Given this, we can say that managers influence the probability of events occurring which might lead to applications being made. The main decision lying behind this is the trade-off between unrestrained managerial authority and the cost of consequent tribunal cases. For example, managers might envisage a workplace governed by few rules and customs, ruled largely by the arbitrary whim of the manager, but this would provide an environment in which feelings of unfair treatment could arise quite frequently. Alternatively, a more regulated, rules-based, workplace would reduce the scope for arbitrary behaviour but may reduce managerial independence.[2]

There are two sets of variables likely to influence the manager's decisions and hence the likelihood of an event leading to an application to an Industrial Tribunal.

- The first set will be the cost to the firm should it lose an action (which will include not only the value of the award but also the administrative time and costs of going to the Tribunal and subsequent harm to the firm's reputation). A high cost will encourage the firm to avoid such cases.
- The second set is the benefit of employment practices that may lead to cases being brought.

This trade-off is likely to be different for different types of firms. In particular, part of the competitive advantage of small firms is their ability to respond flexibly. In general they do not have personnel departments and tend to operate with fewer workplace rules. We might therefore expect small firms to give rise to more actionable events. We denote the number of workers employed in small firms as SF.

A key role of unions is to act as protection for workers against unfair treatment. This collective strength is the most common reason for people joining unions and wishing for union representation at the workplace. We would expect union presence to be associated with a lower number of actionable incidents occurring. This is for three reasons.

- First, firms probably try harder to avoid such incidents if unions are strong.
- Second, where unions are present, management tend to have established procedures in place.
- Third, when they arise, disputes can be dealt with through workplace negotiating channels rather than formal legal mechanisms.

Thus, union presence (*UP*) will negatively influence the number of potential 'trigger' events.

We may also expect the state of the economy to affect the number of cases brought. Falling product demand will increase pressures for cost cutting, while high levels of unemployment may lead to more aggressive management practices.

A final issue relates to the possible role of the legal system itself in contributing to the rise in caseload. In other areas of the public service, the behaviour of the suppliers of the service may lead to an increase in demand. For example, it has been argued that the way legal aid fees have been paid has, until recent changes, increased the volume of cases. In private health care it is argued that doctors have an incentive to give patients more tests than in the NHS. But given the much more informal nature of the proceedings of the IT system and the relatively minor role played by legal professionals, we view this as unlikely to occur in IT cases.

To summarise, we expect the number of potentially actionable incidents to depend on managerial style, the value of flexibility, the number of small firms, the presence of unions, and the general state of the economy. The first two of these are more or less unmeasurable in the aggregate, so we have *Equation 4*:

$$N = N(SF, UP, U) \qquad (4)$$

2.1.3 Industrial and labour force structure

Having set up a general model of the IT application process, we need to take account of the labour market context. At this point we recognise that there are different jurisdictions each with its own special set of circumstances. Also, different people in different conditions will make different decisions on whether or not to make claims. So we need to control for the structure of the labour force to capture some of the more slowly evolving background features of IT cases.

We can get some idea of which groups are more likely to make claims from the periodic surveys of the people bringing cases (see Stevens 1988, Tremlett and Banerji 1994, and Nove 1995).[3] These show that on average men were more

likely to make claims than women (in general that is – for discrimination and equal pay cases women were more likely to bring a case), that the median age of claimants was 39, and that some industries were more prone to cases than others. The more high-risk industries included distribution, retail, hotels, catering, and other services.

A related issue is that the right to bring an unfair dismissal case is not available to all: there is a minimum job tenure requirement and, until 1995, there was a minimum hours per week requirement.

We control for all these background influences by including a set of variables describing the composition of the labour force. These are denoted by *X* and are spelt out in detail below.

2.1.4 Summary

The model is as follows. Economic behaviour has four effects on the total number of applications.

- First, firms and unions jointly influence the nature of the working environment. This influences the number of potentially actionable cases that arise.
- Second, once such an event has taken place, the worker will weigh the costs and benefits of making an application to an IT.
- Third, we expect the worker's probability of success and the expected value of subsequent awards to matter.
- Finally, the structure of the labour force and the nature of the available jobs have a background influence on the number of cases. In short, we expect the presence of unions, the importance of small firms, and some demographic characteristics of the labour force to matter.

The model we take forward to the empirical part of the paper is the following:

Total number of applications is

$$N\pi = g\,(p, V, U, S, L, SF, UP, X) \qquad (5)$$

Where:

- N is the number of potentially actionable incidents,
- π is the probability of bringing a case following a potentially actionable incident,
- p is the average chance of winning a case,
- V is the average value of awards,
- U is the level of unemployment (generally, the state of the labour market),
- S is the level of support for the litigant,
- L is the general level of litigiousness in society,
- SF is the number of workers working in small firms,
- UP is a measure of union presence, and
- X is a set of demographic and industrial structure variables.

2.2 Econometric Modelling

Our intention is to estimate the model outlined in Section 2.1, given the limitations of the data. This model is designed in terms of the level of applications, and this is the basis of our econometric approach. An understanding of the change in the number of applications can be derived from a model in levels, but the reverse is not true. We adopt the following approach.

2.2.1 Analysis of aggregate data

First, we estimate applications for each jurisdiction separately using aggregate data for the years 1985 to 1997. The jurisdictions are defined as unfair dismissals, discrimination, Wages Act, breach of contract, redundancy and other. Given that the profile of the total is basically driven by three facts (the sharp jump in unfair dismissal cases, the steady upward trend in discrimination cases and the steeper upward trend in Wages Act cases – see below for details), the best approach is to model each jurisdiction separately and then simply add the totals.

In some cases the key independent variables were only available up to 1995. Given the small number of data points, and the degree of collinearity between some of the independent variables, the parameters that can be estimated are limited. Also, because there is much less data than we had expected, we are unable to explore any lag structure as thoroughly as we would have liked. Cointegration analysis is pointless with such a small number of observations (11).[4] Furthermore, the standard battery of tests to check for residual serial correlation, heteroscedasticity, parameter constancy and the like are unfeasible with such a small dataset. The following strategy is adopted:

Step 1

All series (dependent variables and regressors) are graphically examined to identify trends and the extent of collinearity. Correlation coefficients are examined to identify regressor series that are particularly highly correlated.

Step 2

The series for total applications within each jurisdiction is regressed on one variable from each of the following sets:

(a) a time trend;

(b) the probability of winning and a measure of the amount won;

(c) labour force characteristics;

(d) occupational structure;

(e) the measure of general litigiousness.

These bivariate regressions allow us to identify correlations with different measures of the labour force and occupational structure.

Step 3

Total applications within each jurisdiction are regressed on the core economic variables (namely, probability of winning and a measure of the award level) plus one other variable from one of the sets of measures of (a) a time trend, (b) labour force and industrial structure, or (c) the measure of general litigiousness.

Step 4

The procedure is repeated using the lagged probability of winning and lagged award to allow for informational lags to affect behaviour.

All analyses are undertaken using OLS.

From this, a limited number of equations are selected to predict future applications for each jurisdiction. The basis for selection of predicting equations is:

- goodness of fit (adjusted R2 and fit of the predictions),
- economic plausibility of the results,
- variables that are in the public domain and for which there are relatively consistent series.

2.2.2 Analysis of regional data

Regional data for the same period are analysed to:

- test the robustness of the aggregate analysis, and
- examine whether it is possible using more data to identify the impact of more than a single measure of labour force or industrial structure.

The strategy adopted is to estimate models using the national probability of winning and the award levels and regional measures of labour force and industrial structure. The overall strategy is similar to that of the aggregate analysis, but reflects the fact that the data available at regional level are slightly different and that (at step 3) the greater number of observations permits estimation of the impact of the marginal effect of a larger number of regressor variables:

Step 1

All series (dependent variables and regressors) are examined graphically to identify trends and the extent of collinearity. Correlation coefficients are examined to identify regressor series that are particularly highly correlated.

Step 2

Total applications within each jurisdiction are regressed on one variable from each of the following sets:

(a) a time trend,

(b) the probability of winning and a measure of the amount won,

(c) labour force and industrial characteristics.

Step 3

Total applications within each jurisdiction are regressed on the probability of winning and a measure of the award level plus at least two other variables from the sets of measures of labour force and industrial characteristics.

Step 4

The procedure is repeated using the lagged probability of winning and lagged award to allow for informational lags to affect behaviour.

From this, a limited number of equations are selected to predict future applications for each jurisdiction, using the same criteria as for the model using national data.

2.2.3 Analysis of unfair dismissals data over a longer period

We use a longer time series to examine in detail the relationship between unfair dismissals and the probability of winning a case. The data cover the time period 1972 to 1995. With this longer time period, we can exploit rather more of the power of econometric testing. We test for serial correlation, heteroscedasticity and (crucially) parameter constancy using recursive least squares techniques.

End Notes

[1] It may be that some events are intended i.e. meant to force the individual to quit their job.

[2] Note that the decision on this trade-off is taken in the light of the firm's view of the workers' behaviour discussed above. That is, the firm is more likely to adopt the former model if it believes that the likelihood of a worker making an application is low.

[3] See Stevens, M. (1988) 'Unfair dismissal cases in 1985-6 – characteristics of the parties in Employment Gazette, December. pp. 651 – 659. Tremlett, N. and Banerji, N. (1994) 'The 1992 Survey of Industrial Tribunal Applications' Employment Department Research Series no. 22. Nove, A. (1995) Industrial Tribunal (England and Wales) Customer Survey 1995' Public Attitudes Surveys Ltd., High Wycombe.

[4] We do provide tests of integration for the quarterly versions of the dependent variables in the Appendix. Even these 48 observations are stretching the utility of such tests; since none of our independent variables have any real quarterly variation, we cannot conduct cointegration analysis.

Three
DATA

In this chapter we describe the data chosen for the analysis and briefly outline the decisions that have led to these choices.

3.1 Dependent Variables

The dependent variable is the number of registered applications to ITs. This derives from the number of 'IT1' forms. The 'IT1' is the form used to make a claim to an Industrial Tribunal and initiate the process. This data was provided by the DTI. Our aim was to increase the number of observations by disaggregating the data both by jurisdiction and by region. The former proved easier than the latter.

3.1.1 Disaggregating the data by jurisdiction

We use data for Great Britain from the Employment Tribunal Service (ETS) for the financial years 1986/7 to 1997/8. As well as using the national total, we examine applications by jurisdiction. Registered applications are recorded under dozens of jurisdictions, but for purposes of analysis these have been grouped into broad categories. The categories within each jurisdiction were decided after consultation with the DTI, and correspond with internal DTI classifications. We attempted to get data from 1975 onwards, but this proved impossible. While quarterly variation is available from 1985, this adds no new information. It was decided, in conjunction with the DTI, that we would work with annual data based on financial years. The jurisdictions are the following:

- *Unfair dismissal.*
- *Redundancy payments and insolvency pay.*
- *Discrimination:* race discrimination, sex discrimination, equal pay, maternity pay and unfair dismissal for pregnancy.[5]
- *Wages Act:* that is, unlawful deductions from wages (from 1985 Q2)
- *Breach of contract* cases could be grouped with the Wages Act cases but we have chosen not to include them in the analysis of national data because the legislation only came into effect in mid-1995. This resulted in an abrupt jump in the total. Modelling this steep jump is difficult. As the breach of contract cases appear to follow the same pattern as cases under the Wages Act, we have modelled only the longer series.
- *Other:* the remainder.

3.1.2 Analysis of regional data

For three of the jurisdictions we use ACAS data that provides a breakdown into 9 regions. The original plan was to use regional ETS data. Unfortunately this was only available in hard copy on a monthly basis and was not suitable for data entry. After consultation with the DTI it was decided to use ACAS data for the regional dependent variable. Several issues arise. We discuss both the problems and the steps undertaken to deal with them.

- *Differences in reporting:* ACAS and ETS data do not correspond. This is because the ETS records each applicant's case once only, under the main jurisdiction heading, whereas ACAS records each jurisdiction under which the applicant brings a complaint. To account for this we have used a deflator, defined as follows:

  (ETS national registered applications)/ (ACAS IT1 registered applications).

This was calculated both for the total number of cases and for each jurisdiction, and separately for each year.

- *Difference in regions:* ACAS and ETS regional boundaries do not correspond. In addition, ACAS has changed its boundaries twice (at the margins) during the time period under analysis. We have calculated and/or adjusted regional statistics in order to ensure maximum consistency across regions and through time.
- *'IT1' versus non-'IT1'cases:* ACAS distinguish 'IT1' from non-'IT1' cases. Non-'IT1' cases are those for which no application has (yet) been made. Due to a change in ACAS policy in July 1990, the number of non-'IT1' cases dropped dramatically. To account for this we have used a deflator, for each jurisdiction each year. The deflator is calculated as follows:

  (IT1 cases only)/(IT1 plus non-IT1 cases).

As the division between IT1 and non-IT1 cases is available only for national data we have deflated the regional totals using the national data.

- *Redundancy and insolvency:* We do not have regional data on this category of claims because ACAS has not provided conciliation in such cases (though following the 1998 Employment Rights (Dispute Resolution) Act this service will be offered in future).
- In this section we do group breach of contract cases with Wages Act cases.

3.1.3 Analysis of longer run data for unfair dismissal

The one series for which we do have a longer run of data is the national unfair dismissal series. This was available from Burgess (1988)[6] and included both the number of applications made and the proportion successful[7] from 1972 (when it was introduced) to 1986. This was combined with the DTI data to give an annual series from 1972 to 1995.

3.2 Independent Variables

We use the model set out above to group the variables that the theory suggests will be useful and list their empirical counterparts.

3.2.1 The average chance of winning a case

The data used include the proportion of cases conciliated, the proportion withdrawn and the proportion successful (for the applicant) of those gone to hearing. This is ETS data from *Labour Market Trends* and *Employment Gazette*. We have both national totals and figures per jurisdiction as defined above. Note that winning at the tribunal hearing is not the only way in which an applicant can be successful. Most ACAS-conciliated cases involve some payment as do about half of the cases withdrawn. The applicant may or may not consider these as successful, and it is difficult to count all such cases as 'wins' for the applicants. Given this, we take as our measure of the probability of success in an application the proportion of cases going to a hearing that are won by the applicant. These data are jurisdiction-specific. Information on success rates is only available at the national level, so for the regional analysis we use the national rates.

3.2.2 The value of awards

We include ETS data on the distribution of compensation awarded, again from Labour Market Trends. The compensation data is only available for unfair dismissal, race discrimination and sex discrimination jurisdictions. We compute the median award for each of these jurisdictions. We use a weighted average of the race and sex case payouts to model discrimination cases in the national analysis. In addition to the median award level, we also use other aspects of the distribution as it may be the high awards that generate a lot of publicity and affect public awareness. For example, in 1994/5, compensation in excess of £8,000 was awarded in over 40% of successful cases of sex discrimination, compared to 17% the following year. We therefore also calculate the proportion of cases awarded an

Name	Empirical Counterpart	Model Symbol	See below for notes:
Expected chance of winning a case	Proportion of cases going to a hearing won by the claimant (jurisdiction specific)	*P*	3.2.1
Expected value of awards	Median award made Proportion of high awards made (jurisdiction specific) Constant prices	*V*	3.2.2
Level of support for the litigant	Union membership rate among all employees	*S*	3.2.3
General level of litigiousness	Number of civil cases brought per year	*L*	3.2.4
State of the labour market	Unemployment rate Redundancy rate Tenure structure of the workforce	*U*	3.2.5
Behaviour of firms and unions	Number of workers employed in small firms (number of workers<25)	*SF*	3.2.6
	Union membership rate	*UP*	3.2.3
Demographic and industrial structure variables	Proportion of employees female Proportion of employees part-time Age structure of employees Tenure structure of employees Industrial structure of employees Occupational structure of employees	*X*	3.2.7

amount over a specified threshold (£9,000 for unfair dismissal, £3,000 for race and £8,000 for sex discrimination). The outcomes data is only available up to and including 1995/96. After discussions with the ETS, several problems with the 1996/97 data emerged which prevent it being used in the analysis. Specifically, only the first three quarters' figures for England and Wales are available: the introduction of a new computer system that year meant that neither accuracy nor consistency could be guaranteed for the fourth quarter data and even these incomplete data are not available for Scotland in that year. Hence the outcome data run from 1985/6 to 1995/6.

3.2.3 Level of support for litigants

This takes a variety of forms. The applicant has to decide whether to settle or go for a full hearing. For a hearing the applicant may want advice or even representation. For most people, this would be a new experience and they would be more likely to undertake this activity with support from their union or other organisation. There is not much information on where people go for their advice.[8] Lacking information on other sources, we look at trade union support. In about 10% of cases, trade unions actually represent the applicant at the hearing. Unions also generally help their members to settle without a hearing. We therefore use information on union membership rates (from *Labour Market Trends*).[9] Union membership fell continuously from 1979 and people will have turned to other sources for advice, such as Citizens' Advice Bureaux, but we do not have any relevant statistics. Our indicator therefore probably underestimates the amount of support available.

3.2.4 General level of litigiousness

Employees and employers can resolve disputes in different ways. The methods range from informal negotiation and conciliation to an immediate resort to formal legal proceedings. The way that employment disputes are dealt with presumably reflects, to a large extent, the way that society in general resolves disputes. We therefore use the number of civil cases brought each year as a general indicator of the resort to law. These statistics have been provided by the Court Service, and report the annual number of proceedings in England and Wales. Comparable data for Scotland proved to be unavailable.

3.2.5 State of the labour market

The general state of the labour market may have an influence on the parties' decisions on whether to make applications to the IT system, and whether to attempt to reduce actionable events. However, the nature of this dependence is not simple. For example, in a tight labour market, firms will be keen to hang on to their workers and not to alienate them. However, in a slack labour market, employers can afford to be more cavalier, but workers may be nervous of acquiring a reputation as a troublemaker and be reluctant to push cases. Thus, while the tightness of the labour market clearly affects the balance of power, it is not necessarily the case that it will lead to fewer IT cases. We measure the general state of the labour market using:

- the claimant unemployment rate (taken from *Labour Market Trends*), and
- the redundancy rate (taken from the Labour Force Survey).

In addition to these factors, people may also be influenced by their feelings of job insecurity.[10] We use data on the distribution of job tenure in the economy to examine this possibility.

3.2.6 The nature of production and management practices

We identified two variables that could affect this: union membership and firm size. Union membership has already been discussed above. Firm size no longer determines eligibility for unfair dismissal claims. But it may be the case that the size of the firm influences the likelihood of an application being made. For example, the personnel affairs of larger firms are generally more regulated by rules and less by managerial whim. We would expect this to reduce the probability that an IT case is brought. Note that the data we have relate to *workplace* size not *firm* size, as this was all we could readily find (from the Labour Force Survey which allows us to identify employees in establishments with fewer than 25 employees). While these are clearly distinct concepts, they are likely to be quite closely correlated over time, since most workplaces are single establishment firms. Similarly a minority of workplaces are part of multi-establishment organisations.

3.2.7 Demographic and industrial structure variables

The chance of an individual experiencing an event perceived to be unfair and then taking an application to an IT might depend on personal characteristics. Aggregating up to the workforce as a whole, the total number of applications will depend on the composition of the workforce. For example, the number of applications in equal pay cases may depend on the proportion of women in

the workforce. We take account of this by including in the dataset:

- the proportion of women,
- the age structure,
- the industrial and occupational structure, and
- the balance between full-time and part-time workers.

The national labour market statistics are all from the *Labour Force Survey, 1998 Historical Supplement*. These have been supplemented by regional statistics taken from Regional Trends.

Part of the way that 'composition effects' may work, is through eligibility rules. The right to bring cases to an IT varies between the different jurisdictions. The right to bring an unfair dismissal action has eligibility criteria that have changed considerably over time since the right came into force in February 1972. The initial qualifying period was at least two years employment with the employer (working at least 16 hours per week), reduced to one year in 1974 and six months in 1979. It was then raised back to one year in 1979, and to two years in 1980 for firms employing fewer than 20 people, then in 1985 to two years for all full-time employees. The hours threshold was removed in 1995. These multi-dimensional criteria make determining the size of the eligible population for the most common type of action complex. Rather than trying to construct a measure of the covered population, we simply include the compositional controls separately.

End Notes

[5] Recorded as RRD, SXD, EQP, MPY, U60 in ETS management information.

[6] Burgess, S (1988) Employment Adjustment in UK Manufacturing. Economic Journal 98, pp. 81-103.

[7] From 1985 in the data provided by the DTI we have used the proportion of cases won by the worker as the measure of success. From Burgess' data we have the proportion gaining monetary compensation. Since the number of successes requesting reinstatement is relatively small we did not feel too uncomfortable simply joining these two together.

[8] We were unable to follow up the issue of whether public perceptions on the role of the Equal Opportunities Commission and the Commission for Racial Equality had changed much in this regard.

[9] From 1989 we use measures derived from the Labour Force Survey. For earlier years we have constructed a series derived from trade union membership as recorded by the Certification Officer. This can only be done for the analysis of national data.

[10] However, it is clear that individuals' anxiety about the security of their jobs remained high even though the evidence suggested that in fact the situation was barely changing. We had hoped to use the number of newspaper articles about the subject, but in the event did not follow this up.

Four
RESULTS

Before presenting the results of the analysis it is necessary to stress the limitations imposed on the analyses by the data available. As Chapter 3 explained, we have encountered several problems that have led to the quantity of data, and hence number of observations, being less comprehensive than was originally planned.

- First, pre-1985 data on applications to tribunals are not available, nor post 1995/96 outcomes data. This reduces the number of annual observations to 11.
- Second, the poor quality of the regional ETS data means we have to use ACAS figures which raises issues of comparability between the national and regional analysis.

We have adjusted our methodology in order to account for these difficulties where possible.

4.1 Aggregate National Data

Step 1. Graphical analysis

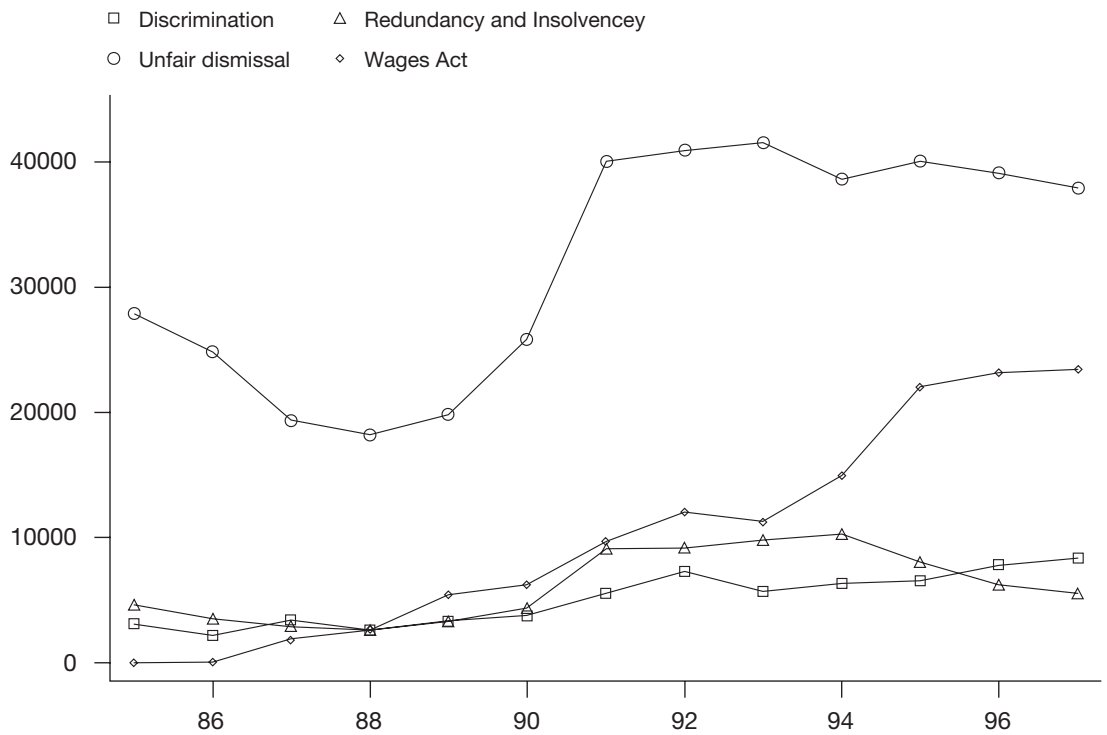
a) Applications to industrial tribunals

Figure 1 showed the pattern in total applications across the years of the sample. These fall between 1986/87 and 1988/89; they rise rapidly to 1991/92, then less rapidly up to 1996/97, and have a slight fall in the final year.

Examination of the separate jurisdictions that make up the total number of applications indicates that there are quite different patterns across the jurisdictions, and that the shape of total jurisdictions is driven by the different behaviour across jurisdictions.

Figure 2 shows that both discrimination and Wages Act cases rise during the period, the latter more sharply than the former. On the other hand, unfair dismissal cases show a fall from 1985/86 to 1988/89, followed by a sharp rise up to 1992/93, levelling off thereafter. Redundancy cases increase in the early 90s, fall thereafter. Given the relative size of the jurisdictions, the overall shape is determined by the movement in unfair dismissals cases, with the spikes in total numbers in 1986/87 and 1996/97 being due to the exceptional number of "other" jurisdictions.

Figure 2: Total applications by jurisdiction (excluding other)



b) Success of cases

For the employee considering taking action, the proportion of cases that are settled, withdrawn or are successes at tribunal hearing is important. *Figure 3* shows the breakdown of the total caseload into the numbers that were conciliated by ACAS, withdrawn and went to hearing. Up to 1990 the proportions in each of these three categories were similar. After 1990 the proportion going to ACAS fell, whilst the proportions that were withdrawn or went to hearing remained similar. Within jurisdictions the patterns in these proportions have stayed pretty similar throughout the period (with the exception of unfair redundancy and insolvency, where only a handful of cases have gone to ACAS). The proportion of cases that are settled, withdrawn and gone to hearing has remained stable throughout the period.

Figure 3: Destination of all cases

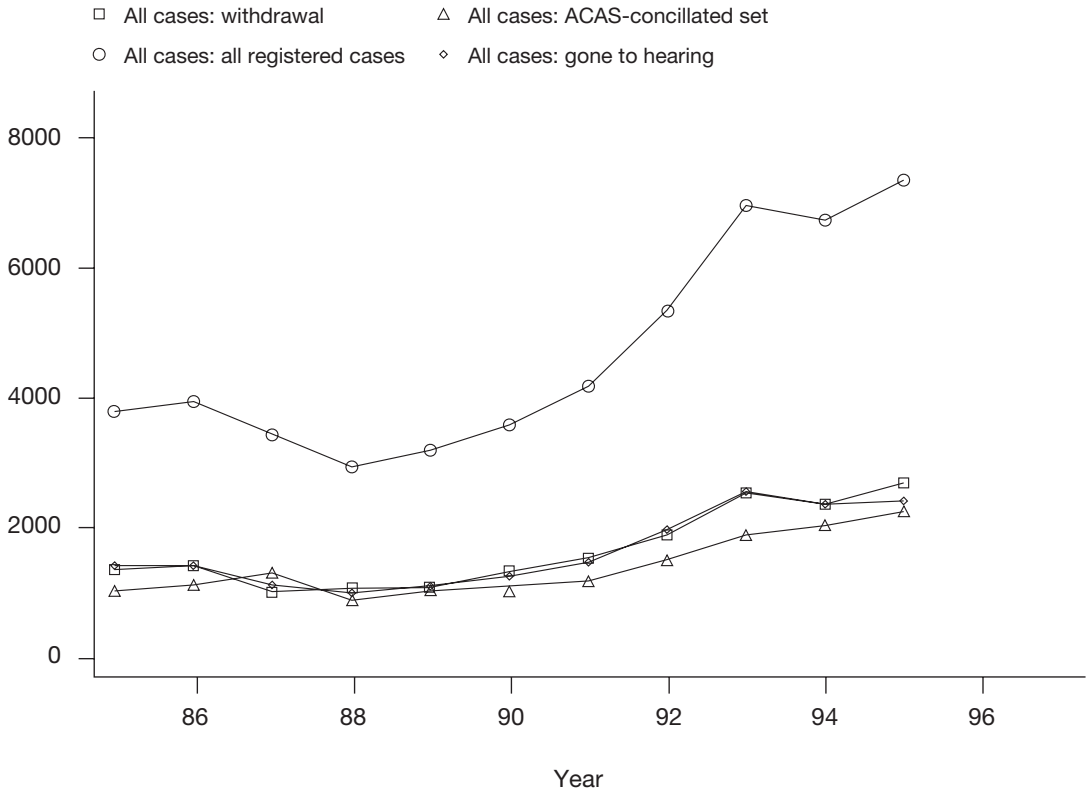


Figure 4 plots the success rate, where the denominator is the total cases going to hearings and the numerator is the number of decisions in favour of the applicants. While this measure does not account for all successes (for example, some cases settled before a hearing can be thought of as a success for the applicant), it is perhaps the best hard measure we have. The proportion of successes at tribunal hearings behaves quite differently to the proportions settled or withdrawn: it rises quite markedly up to 1991 then levels off before falling. Comparison of *Figures 1 and 4* supports our approach.

This aggregate pattern masks considerable variation in the proportion of cases at the level of each jurisdiction. Figure 5 shows the proportion of cases brought to tribunal that were successful by jurisdiction. The proportion is quite different across jurisdictions. The applicant whose case gets to tribunal is most likely to be successful in a redundancy or insolvency case and least likely to be successful in a race or sex discrimination case. There is also a difference in the proportion of cases withdrawn (picture not shown). Redundancy and insolvency have the highest withdrawal rates and Wages Act/breach of contract cases the lowest. There appear to be differences in trends across jurisdictions too: there has been a fall in the proportion of redundancy and insolvency cases that are withdrawn but a rise in the proportion of race and sex discrimination cases.

Figure 4: All cases: Percentage of tribunal cases that were successful

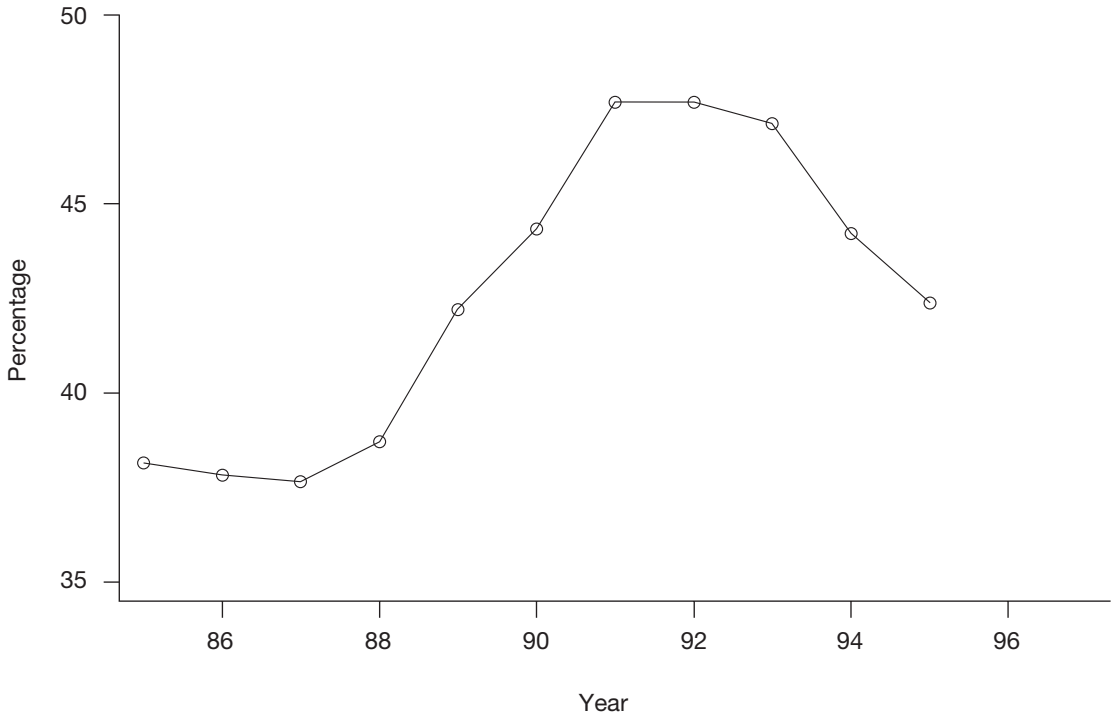
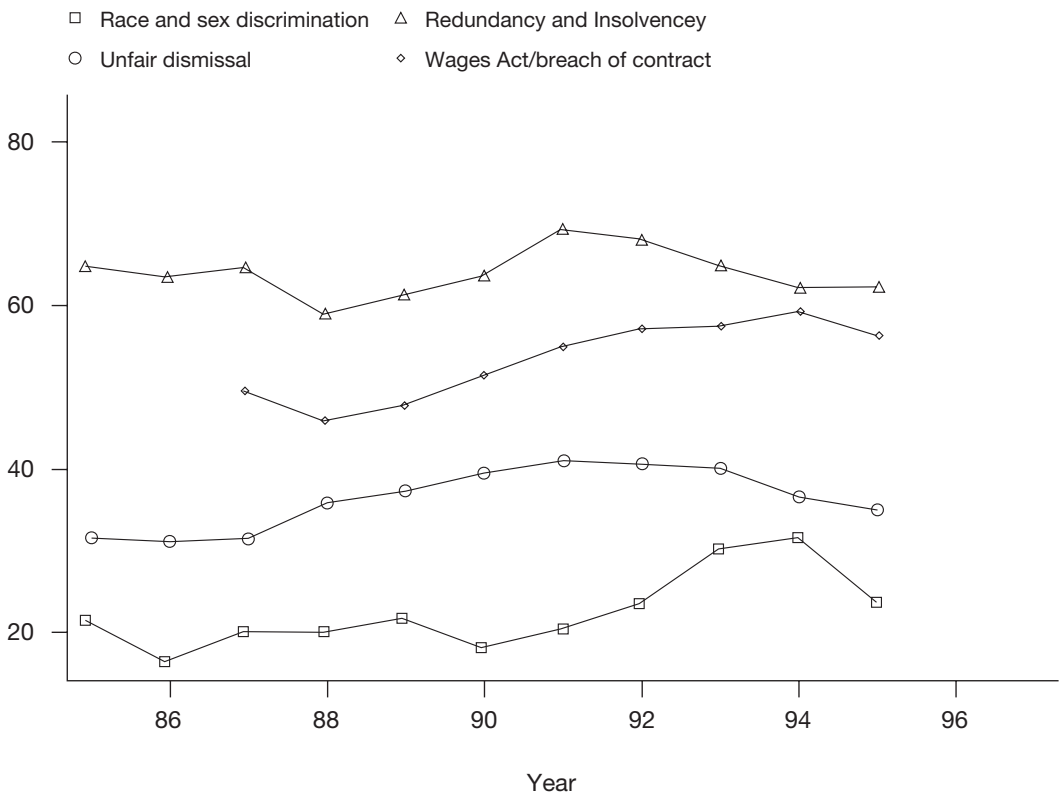


Figure 5: Percentage of tribunal cases that were successful: by jurisdiction



c) The distribution of payments

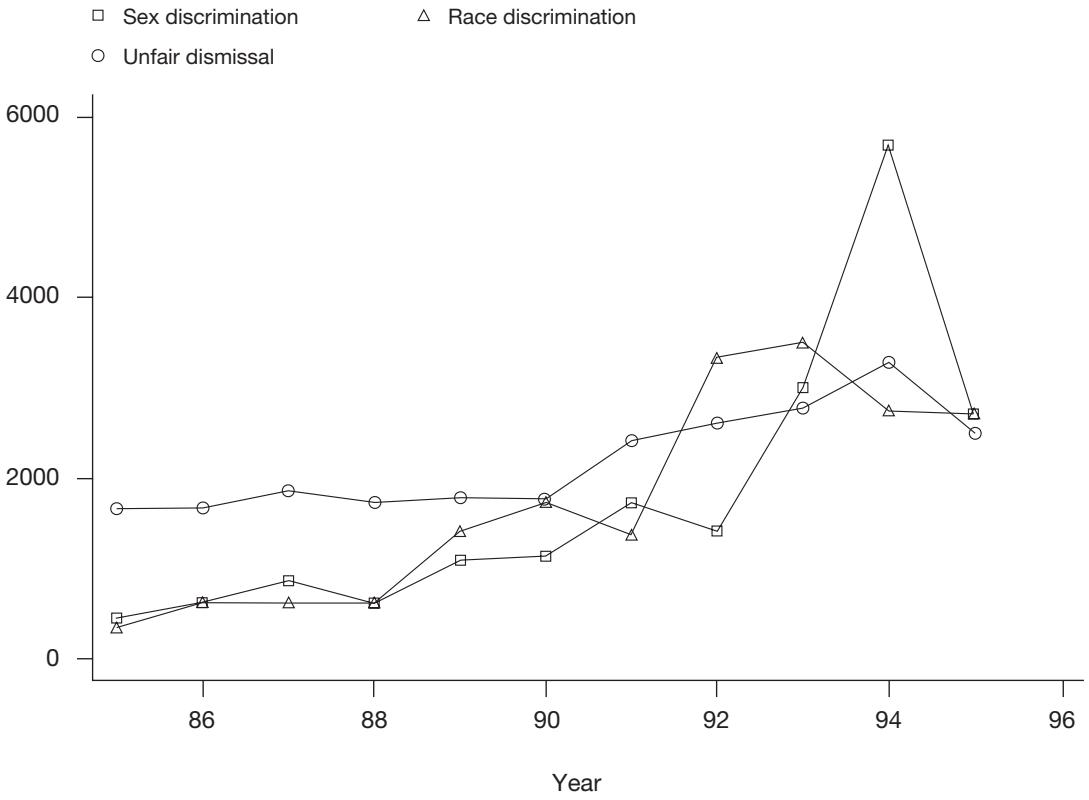
Figures 6 and 7 show indicators of the award levels i.e. the expected payment an applicant would get should their case be successful. These are only available in the jurisdictions given in the figures up to 1995. We do not have figures for Wages Act or Redundancy Payments. In the statistical analysis we use inflation adjusted, i.e. real payments, but here we look at both current and constant prices.

Figure 6 shows median awards. It is clear that the absolute (non-inflation adjusted) level of the award has risen in all jurisdictions and the rate of increase has been greater for discrimination than unfair dismissal cases. The constant price series show the same long-term pattern, although the initial slight rise in unfair dismissal payments is turned into a slight fall and the rise in discrimination payments is slower. In the earlier years, median payouts for sex and race discrimination were considerably lower than those for unfair dismissal. By the end of the period the payouts were very similar (ignoring the spike in 1994/95).[11]

Figure 7 shows the proportion of awards over a certain sum in current prices (the sum varying by jurisdiction). The higher proportion in the chart for race cases reflects the lower sum of £3,000 that is recorded for race discrimination cases. It is clear that the distribution of awards in all jurisdictions has shifted towards higher payouts. It is also clear that this has been stronger in both race and sex discrimination cases following the removal of statutory limits in 1993, but in both jurisdictions this has been subsequently reversed. Nevertheless, in both, payments are trended upwards.

Figure 6: Median awards by jurisdiction

(a) Current prices



(b) Constant prices

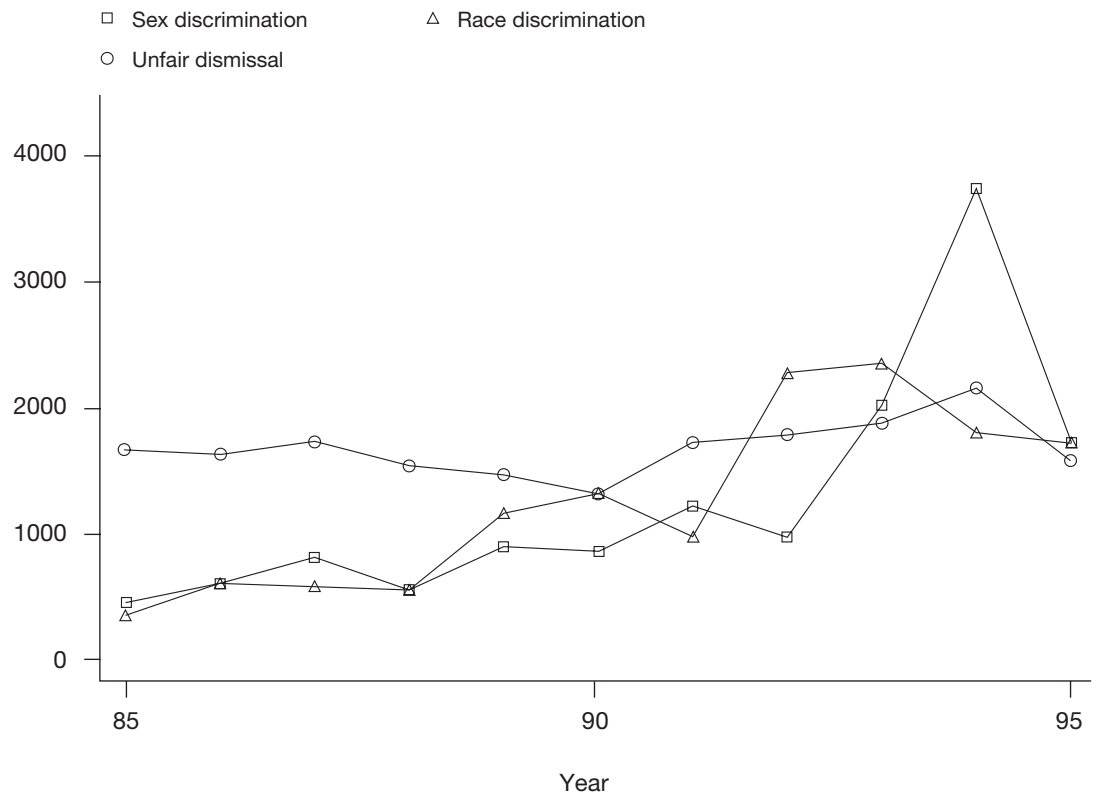
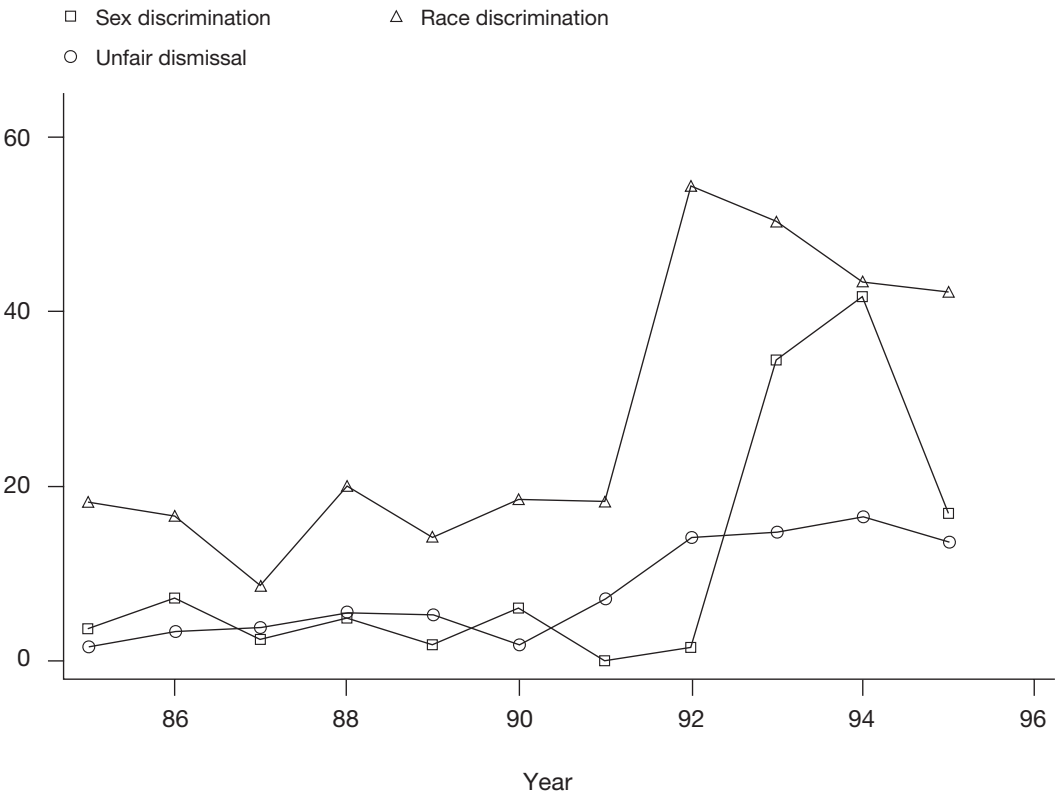


Figure 7: Proportion of awards over £9000 (unfair dismissal), over £3000 (race discrimination) and over £8000 (sex discrimination)



d) State of the labour market

The claimant unemployment rate is shown in Figure 8. From a high of 10.8% in 1986/87 it fell to 5.7% in 1990, before rising back to 10% in 1994/95. This pattern does not appear to fit with the number of applications either in total or in any of the separate jurisdictions. This is shown by Figure 9 which cross-plots the number of applications against the unemployment rate, and also more formally by the regressions in *Table 2*.

Figure 8: Unemployment rate

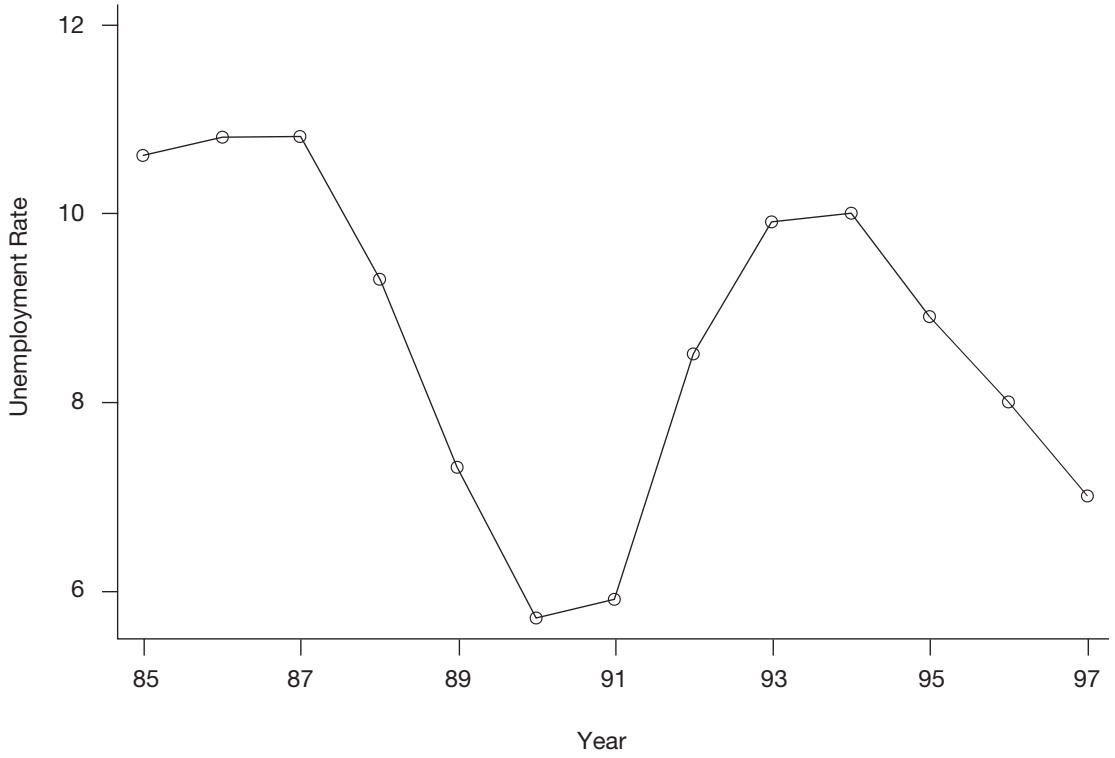


Figure 9: Number of applications and the unemployment rate

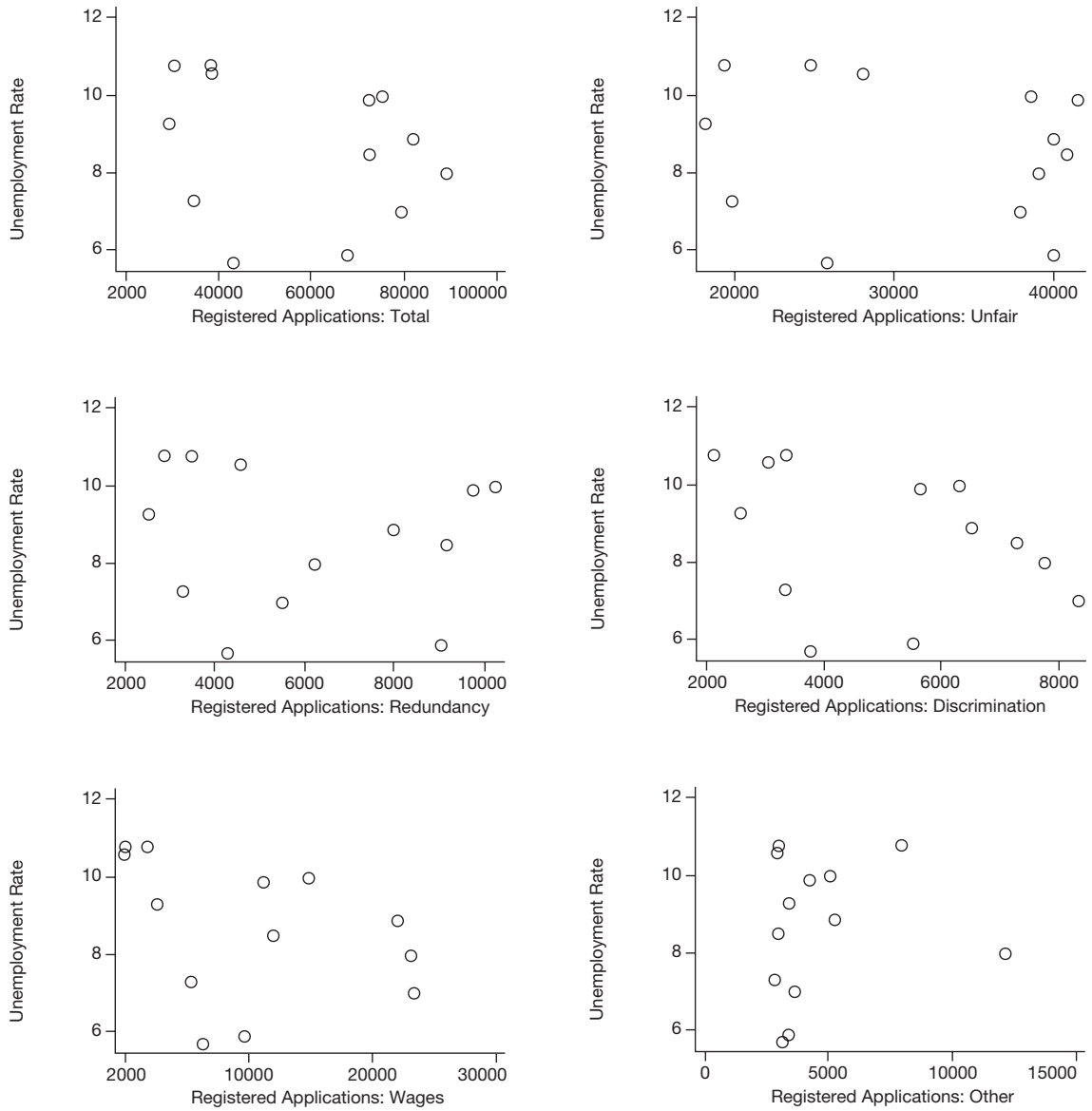


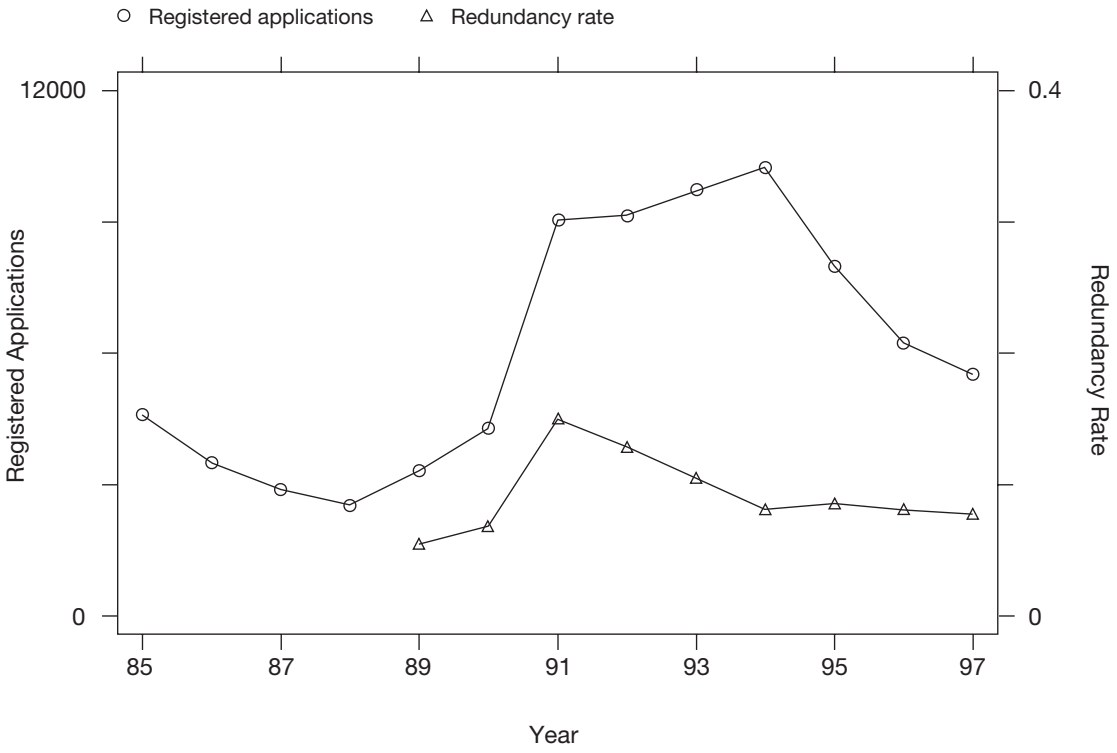
Table 2: Bivariate regressions for each jurisdiction

		Proportion of labour force that are:												
Jurisdiction:	***Trend***	***Tenure: under 1 year***	***Tenure: 1-2 years***	***Tenure: 2-5 years***	***Part-time***	***Female part-time***	***Female***	***Age: 16-24***	***Age: 25-49***	***Age 50+***	***Union members***	***Unem-ployed***	***Redun-dancy rate***	***Civil***
Unfair dismissals	+0.59				+0.60	+0.40	+0.69	-0.76	+0.73		-0.58		+0.43	
Sex and race discrimination	+0.87	+0.34			+0.87	+0.53	+0.82	-0.88	+0.84		-0.84			
Redundancy and insolvency	+0.37			+0.33	+0.37		+0.57	-0.53	+0.58		-0.39		+0.48	
Wages act/breach of contract	+0.95		-0.28		+0.94	+0.55	+0.80	-0.91	+0.87		-0.92			
Other						+0.28								
Total applications	+0.83	+0.35	-0.33		+0.85	+0.56	+0.84	-0.94	+0.90		-0.81			
N	13	12	12		13	13	13	13	13	13	13	13	9	13

Note: (1) Cell is blank if coefficient is insignificant
(2) Figure reported is R2 and sign of coefficient

A reasonable starting point for modelling the series of applications under the redundancy payment jurisdictions is to look at the number of people being made redundant. It also seems likely that insolvencies will be correlated with redundancies and the business cycle. *Figure 10* shows that this is indeed the case: the sharp jump in redundancies in 1991, with the onset of the recession, is mirrored in the rise in redundancy claims in that year.

Figure 10: Redundancy rate and redundancy applications



e) Nature of management practices

We identified two measures that could have a bearing on the nature of workplace practices and procedures: trade union presence and the proportion of employees who were in small establishments. Figure 11 shows that union membership fell continuously in the period under consideration (which could cause difficulties in distinguishing it from a time trend).[12] In contrast the proportion of employees in establishments with fewer than 25 employees shows quite a lot of variation. It fell in the second half of the 1980s then returned to previous levels with the recovery of the 1990s, but began to fall off again from 1995.

f) Structure of industry and labour force

Figures 12 and 13 show the industrial and labour force structure. The decline in manufacturing employment is very evident as is the rise in other sectors, most notably distribution, hotels and restaurants, and banking and finance. The proportion in transport and communications has risen a little and the proportion in other services is a noisy series with little absolute change.

Labour force characteristics exhibit strong trends. Women as a proportion of all employees rose (though the rise stopped in 1995) as did the proportion in part-time work. The proportion of the workforce in the 25-49 age band rose while, in contrast, the proportion aged 16-24 fell dramatically. The proportion aged 50 and over has risen slowly since 1988.

Figure 11: Union membership

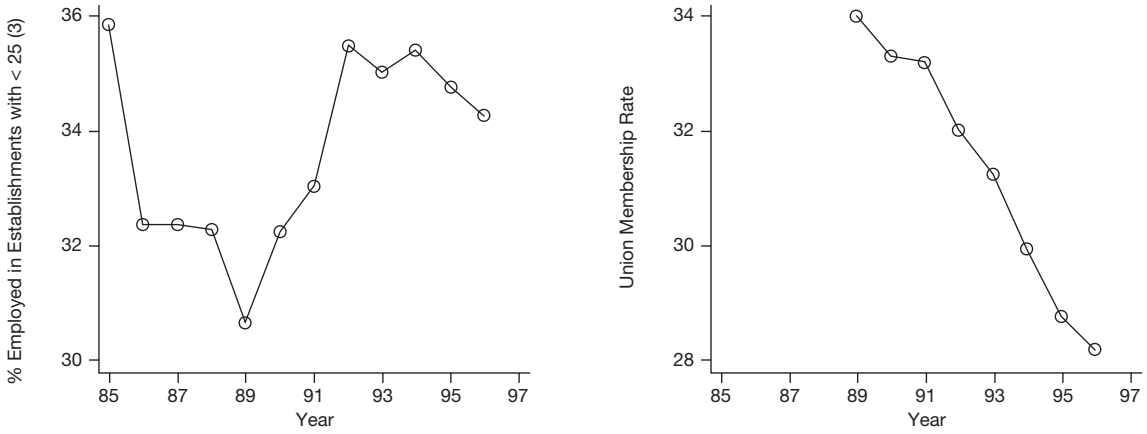


Figure 12: Industrial structure variables. Employment by Industry

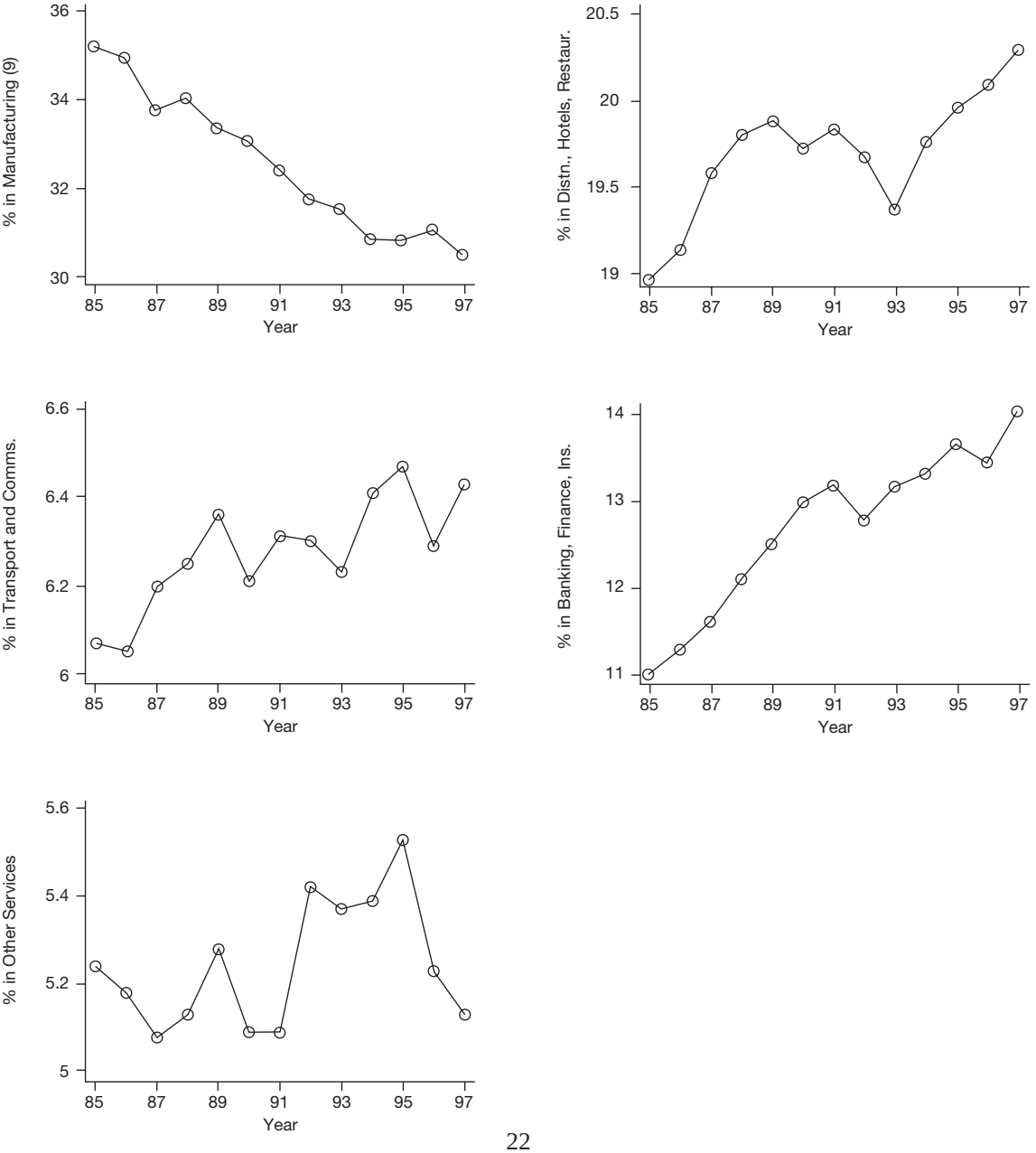
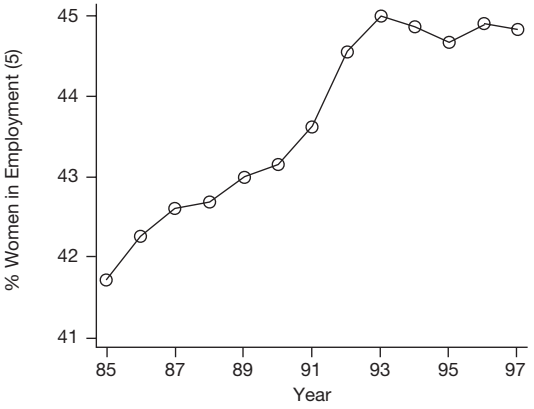
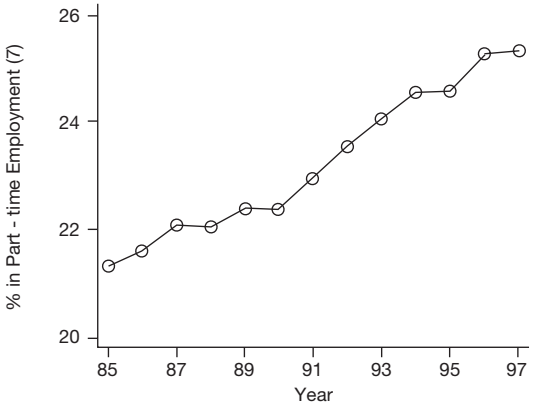
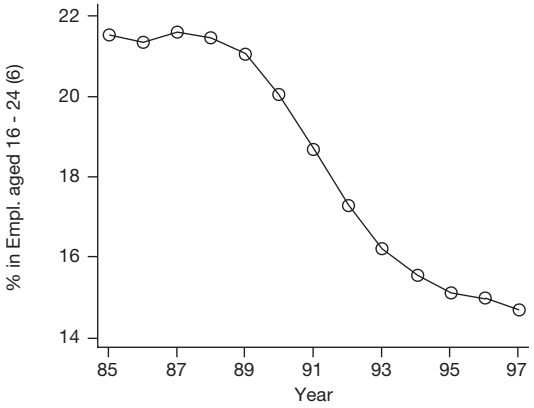
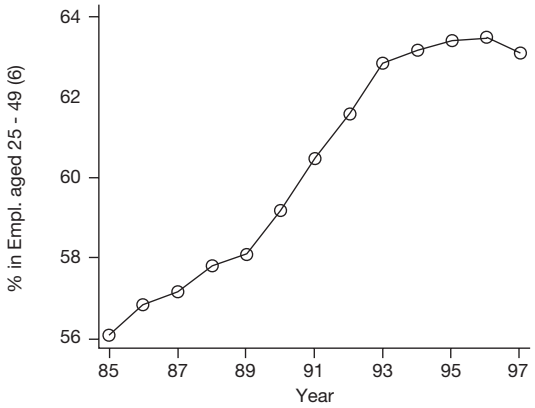


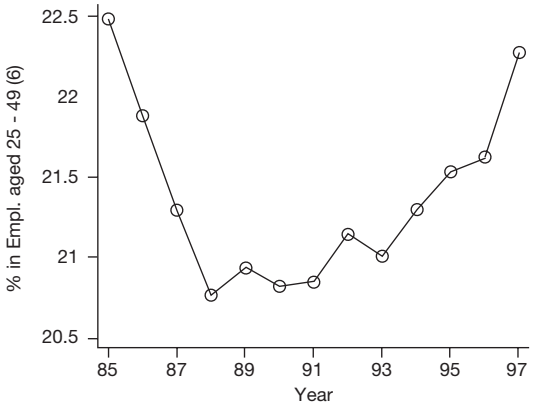
Figure 13: Labour force structure variables











Step 2. Statistical analysis using one independent variable

Tables 2 and 3 show the summary results of bivariate regressions of total applications within jurisdictions on:

- a time trend,
- labour force characteristics,
- measures of industrial structure,
- measures of occupational structure and
- measure of general litigiousness.

The rows of the tables are the jurisdictions, the columns the regressor variables. A non-blank entry in the table gives the adjusted R2 from the bivariate regression of the number of applications on the measure and the sign of the effect in the regressions where the measure has a statistically significant association (at 5% level) with the number of applications.[13] Blank entries indicate that the measure in question is not statistically significant.

Note that the unemployment rate has no significant effect in any jurisdiction. The results show that a relatively high proportion of the variation in applications within several of the jurisdictions can be statistically explained by a simple linear time trend. However, it is also clear that the demographic composition of the labour force, union membership, and industry structure also account for a reasonable amount of the variation. In our focus on economically meaningful explanations we prefer to use measures of labour force, industrial structure and union membership rather than a time trend.

The tables also indicate differences across jurisdictions in the importance of these variables. Labour force composition appears most heavily correlated with discrimination and Wages Act cases. Industry structure is most heavily correlated with the same two jurisdictions. However, from the graphical analysis it is evident that both these jurisdictions show the strongest linear trend and that there is a clear linear trend in labour force composition and industrial structure. So these high correlations are not surprising.

Table 3:

Jurisdiction	*SMEs*	*Industrial structure:* *Other services*	*Trans-port*	*Manuf'g*	*B'ing/ finance*	*Dist'n etc.*	*Occupational structure:* *Manag-ers*	*Soc2*	*Soc3*	*Soc4*	*Soc5*	*Soc6*	*Soc7*	*Soc8*	*Soc9*
Unfair dismissals	+0.54	+0.28		-0.63	+0.49				-0.66						+0.46
Sex and race discrimination	+0.30		+0.48	-0.86	+0.71	+0.42			+0.49			+0.44	+0.74		-0.70
Redundancy and insolvency	+0.49	+0.38		-0.50	+0.35				-0.48				-0.88		+.74
Wages act/breach of contract			+0.61	-0.88	+0.81	+0.56	+0.64		+0.63	-0.72	-0.72	+0.78	+0.58		-0.88
Other									+0.52						
Total applications	+0.35	+0.26	+0.38	-0.82	+0.68	+0.26	+0.61	+0.68		-0.79	-0.72	+0.74			-0.70
N	11	13	13	13	13	13	7	7	7	7	7	7	7	7	7

Note: (1) Cell is blank if coefficient is insignificant
(2) Figure reported is R2 and sign of coefficient
(3) SMEs = small and medium enterprises

Steps 3 and 4 Multiple regressions and lags

a) Unfair dismissal cases

Tables 4-6 present estimates of the following model:

$$UFD = a_1 + a_2\varphi\ UFDt + a_3RMAUFD_t + a_4X_t + e_t \qquad (6)$$

where:

- UFD = unfair dismissal applications,
- φ = probability of winning,
- RMA = real median award,
- t indexes the year,
- e = white noise error,
- X = one of the set of either industry, labour force or occupational characteristics that we hypothesise will affect the number of cases,
- a = constant,
- $a_2 - a_4$ = coefficients.

Table 4: Unfair dismissal applications

Variable	*Probability of winning t-stat*	*Real median award t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	2.2	2.3		0.49	11
Trend				0.58	13
Number of civil cases		2.2		0.6	11
Labour force characteristics (percentages in each category)					
Tenure < 1 year	2.1	2.2		0.42	11
Tenure 1-2 years	3.2		-2.0	0.63	11
Tenure 2-5 years					11
Female					11
Part-time					11
Female part-time	3.5		2.4	0.68	11
Age 16-24			-3.0	0.75	11
Age 25-49			2.1	0.65	11
Age 50+	3.8	2.2	2.5	0.69	11
Union membership				0.73	11
Redundancy rate			2.3	0.63	7
Industry characteristics (percentages)					
Small and medium size enterprises	2.9		2.7	0.71	11
Other services	2.3		1.9	0.62	11
Transport		2.1		0.42	11
Manufacturing				0.55	11
Banking and finance		2.1		0.52	11
Distribution	2.0	2.1		0.43	11
Occupational structure (percentages)					
Managers	8.9	-6.9	6.9	0.96	5
2	2.6	-2.2	1.95	0.61	5
3	2.0	-2.1		0.52	5
4	4.4	-3.43	-3.4	0.85	5
5	12.3	-9.0	-9.6	0.98	5
6	10.4	-6.3	8.0	0.97	5
7	2.0			0.54	5
8	2.5	-2.4	1.97	0.62	5
9	3.8	-1.9	-3.0	0.62	5

Note: Pattern using percentages of awards greater than £9000 very similar (in fact R2 slightly higher, but since not inflation adjusted and bands may change use median award instead).

Signs for occupation on award levels almost always incorrect - possibly due to the shortness of time period for which we have these observations.

Table 5: Unfair dismissal applications

Variable	*Lagged probability of winning t-stat*	*Lagged real median award t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	3.8			0.60	11
Trend	2.1		2.3	0.73	13
Number of civil proceedings	2.6			0.57	11
Labour force characteristics (percentages in each category)					
Tenure < 1 year	3.7			0.56	11
Tenure 1-2 years	3.8			0.70	11
Tenure 2-5 years	3.5			0.62	11
Female			2.5	0.76	11
Part-time	2.6		2.6	0.76	11
Female part-time	4.2		2.4	0.75	11
Age 16-24			-3.7	0.85	11
Age 25-49			3.1	0.81	11
Age 50+	5.4		2.3	0.74	11
Union membership	2.0			0.79	11
Redundancy rate		2.3	2.5	0.60	8
Industry characteristics (percentages)					
Small and medium size enterprises			2.9	0.80	11
Other services	2.1			0.56	11
Transport	3.3			0.55	11
Manufacturing				0.71	11
Banking and finance				0.62	11
Distribution	3.6			0.55	11

Note: Pattern using percentages of awards greater than £9000 very similar (in fact R2 slightly higher, but since not inflation adjusted and bands may change use median award instead).

Table 6: Unfair dismissal applications

Variable	*Lagged probability of winning t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	3.9		0.59	11
Trend	2.2	2.8	0.77	13
Number of civil proceedings	3.8		0.62	11
Labour force characteristics (percentages in each category)				
Tenure < 1 year	3.9		0.59	11
Tenure 1-2 years	4.1	-2.2	0.71	11
Tenure 2-5 year	3.8		0.63	11
Female		3.1	0.79	11
Part-time	2.9	3.2	0.80	11
Female part-time	4.5	3.0	0.78	11
Age 16-24	2.3	-4.3	0.86	11
Age 25-49		3.7	0.83	11
Age 50+	5.9	2.9	0.77	11
Union membership	1.9	-2.1	0.76	11
Redundancy rate			0.27	8
Industry characteristics (percentages)				
Small and medium size enterprises	2.2	3.3	0.81	11
Other services	2.8		0.60	11
Transport	3.1		0.54	11
Manufacturing		-2.5	0.74	11
Banking and finance			0.64	11
Distribution	3.6		0.54	11

Note: Pattern using percentages of awards greater than £9000 very similar (in fact R2 slightly higher, but since not inflation adjusted and bands may change use median award instead).

In Table 5 the probability of winning and the level of the award are lagged by one year. *Table 6* presents estimates without the real median award. The tables report the t-statistic[14] on each of the estimated parameters where significant, the adjusted R2 and the number of observations in the regression. The tables indicate:

- the importance of the probability of winning – both current and lagged levels are statistically significant, though the explanatory power of models with lagged probability is slightly higher;
- the relative unimportance of the real level of the award – this is often insignificant, and in the regressions using only the years 1991 to 1996 it is of the opposite sign than expected;
- the importance of the demographic structure of the labour force – in particular the proportion in the youngest age group (16-24), the proportion female and proportion part-time;
- the importance of industrial structure – in particular the proportion of employees who are in banking and finance and in distribution and hotels;
- the importance of union membership.

On the basis of these results, four models are selected as the preferred models for forecasting unfair dismissals. All models have an economic driver – the lagged probability of winning an unfair dismissal case – plus another variable. These variables are: the proportion of employees aged 16-24, the proportion of the employees who are part-time, the proportion of employees who are employed in small establishments, and a linear time trend.

The coefficient estimates are given in *Table 7* and the plot of fitted versus actuals in *Figure 14*.

Table 7: Preferred models for unfair dismissal

(a) Lagged probability of winning plus the proportion of the workforce aged 16-24

Unfair dismissals applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lag probability of winning UFD case	954.84	412.94	2.31
% labour force Age 16-24	-2417.85	568.47	-4.25
Constant	41547.49	23274.13	1.79
Adjusted R^2	0.86		
N	11		

(b) Lagged probability of winning plus the proportion of the workforce part-time

Unfair dismissals applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lag probability of winning UFD case	1297.48	453.25	2.86
% labour force part-time	4359.19	1372.64	3.18
Constant	-116739.4	26604.41	-4.39
Adjusted R^2	0.80		
N	11		

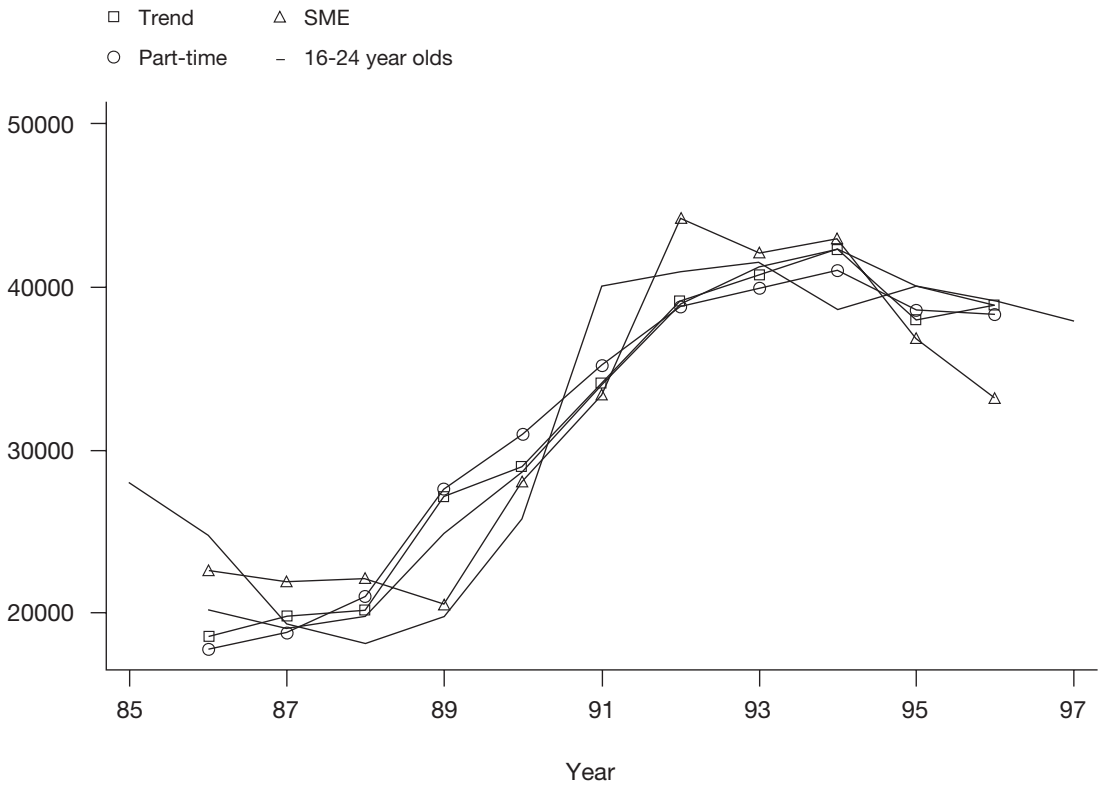
(c) Lagged probability of winning plus the proportion of the workforce part-time in small and medium sized enterprises

Unfair dismissals applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lag probability of winning UFD case	1061.88	480.93	2.21
% labour force employed in SMEs	3732.94	1121.70	3.33
Constant	-131867.5	29489.69	-4.47
Adjusted R^2	0.81		
N	11		

(d) Lagged probability of winning plus a linear trend

Unfair dismissals applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lag probability of winning UFD case	1168.81	520.76	2.24
Trend	1653.42	589.44	2.81
Constant	-161346.1	44179.46	-3.65
Adjusted R^2	0.77		
N	11		

Figure 14: Fitted and actual values: unfair dismissal cases



b) Race and Sex Discrimination cases

A preliminary analysis of this category found that equations with *both* the probability of winning and the real median level of award (or the proportion of cases with awards over a certain sum) did not fit the data well. Accordingly, models were estimated with *either* the probability of winning or the real median level of award.

$$D_t = a_1 + a_2\varphi\, D_{t-1} + a_4X_t + e_t \qquad (7)$$

Table 9 presents estimates of the following model:

$$D_t = a_1 + a_3RMAD_{t-1} + a_4X_t + e_t \qquad (8)$$

where:

- D = discrimination (race plus sex discrimination) cases,
- φ = probability of winning,
- t indexes the year,
- e = white noise error,
- RMA, the real median award, is a weighted sum of the awards for race and sex discrimination cases, with the weights being the annual proportion of cases of each type,
- X = one of the sets of either industry, labour force or occupational characteristics that were hypothesised, based on the bivariate analyses and our economic model, to affect the number of cases,
- a = constant,
- $a_2 – a_4$ = coefficients.

Tables 8 and 9 report the t-statistic on each of the estimated parameters where significant, the adjusted R^2 and the number of observations in the regression. They indicate:

- the lack of importance of the probability of winning – the lagged probability of winning is often not significantly associated with the level of applications and often has the incorrect (negative) sign;
- the importance of the lagged real median award;
- the importance of labour force composition: the proportions of the labour force who are female, part-time or young are significantly associated with the level of applications;
- that industry structure is sometimes important;
- that it is difficult to identify a separate significant effect for both the monetary values of the awards and other variables such as labour force characteristics, as all these variables, and the dependent variable display a linear trend over the estimation period.

Table 8: Discrimination applications

Variable	*Lagged probability of winning t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	1.7		0.15	11
Trend	-1.9	7.2	0.87	11
Number of civil cases	2.1		0.23	11
Labour force characteristics (percentages in each category)				
Tenure < 1 year			0.15	11
Tenure 1-2 years			0.07	11
Tenure 2-5 years	1.7		0.12	11
Female		6.7	0.86	11
Part-time	-1.9	6.9	0.86	11
Female part-time		2.0	0.37	11
Age 16-24	-3.2	-9.2	0.92	11
Age 25-49	-2.4	8.0	0.89	11
Age 50+			0.05	11
Union membership		-5.8	0.85	11
Redundancy rate	1.6	1.7	0.24	11
Industry characteristics (percentages)				
Small and medium size enterprises		3.3	0.59	11
Other services			0.21	11
Transport			0.23	11
Manufacturing	-1.9	-7.8	0.89	11
Banking and finance		3.2	0.58	11
Distribution			0.23	11

Table 9: Discrimination applications

Variable	*Lagged real median t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	3.0		0.45	11
Trend		4.7	0.84	11
Number of civil cases	3.3	1.4	0.51	11
Labour force characteristics (percentages in each category)				
Tenure < 1 year	1.9		0.38	11
Tenure 1-2 years	2.1		0.38	11
Tenure 2-5 year	3.1		0.46	11
Female		4.6	0.83	11
Part-time		4.3	0.81	11
Female part-time	1.5	1.4	0.50	11
Age 16-24		-4.7	0.83	11
Age 25-49		4.7	0.84	11
Age 50+	2.8		0.38	11
Union membership		-3.3	0.83	11
Redundancy rate	1.9	1.5	0.52	8
Industry characteristics (percentages)				
Small and medium size enterprises	1.0	2.4	0.64	11
Other services	1.6		0.40	11
Transport	1.6		0.39	11
Manufacturing		5.4	0.87	11
Banking and finance		2.1	0.59	11
Distribution	2.2		0.42	11

Note: Real median award is a weighted average of the race and sex discrimination awards, weighted by the number of applications.

On the basis of these results, we select four models as the preferred models for forecasting unfair dismissals. All models have only one explanatory variable (in addition to the constant). These are:

- the (lagged) real median level of award,
- the proportion of employees who are female,
- the proportion of employees who are aged 16-24
- the proportion of employees who are employed in banking and finance.

The coefficient estimates are given in *Table 10* and the plot of fitted versus actuals in *Figure 15*.

Table 10: Preferred models for race and sex discrimination

(a) Lagged probability of winning plus the proportion of the workforce aged 16-24

Discrimination applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged real median award	1.73	0.57	3.02
Constant	2778.44	839.19	3.31
Adjusted R^2	0.45		
N	11		

(b) Proportion of labour force female

Discrimination applications	*Coefficient*	*Std. Err.*	*t-statistic*
Proportion of labour force female	1639.51	227.54	7.21
Constant	-66542.87	9939.84	-6.70
Adjusted R^2	0.81		
N	13		

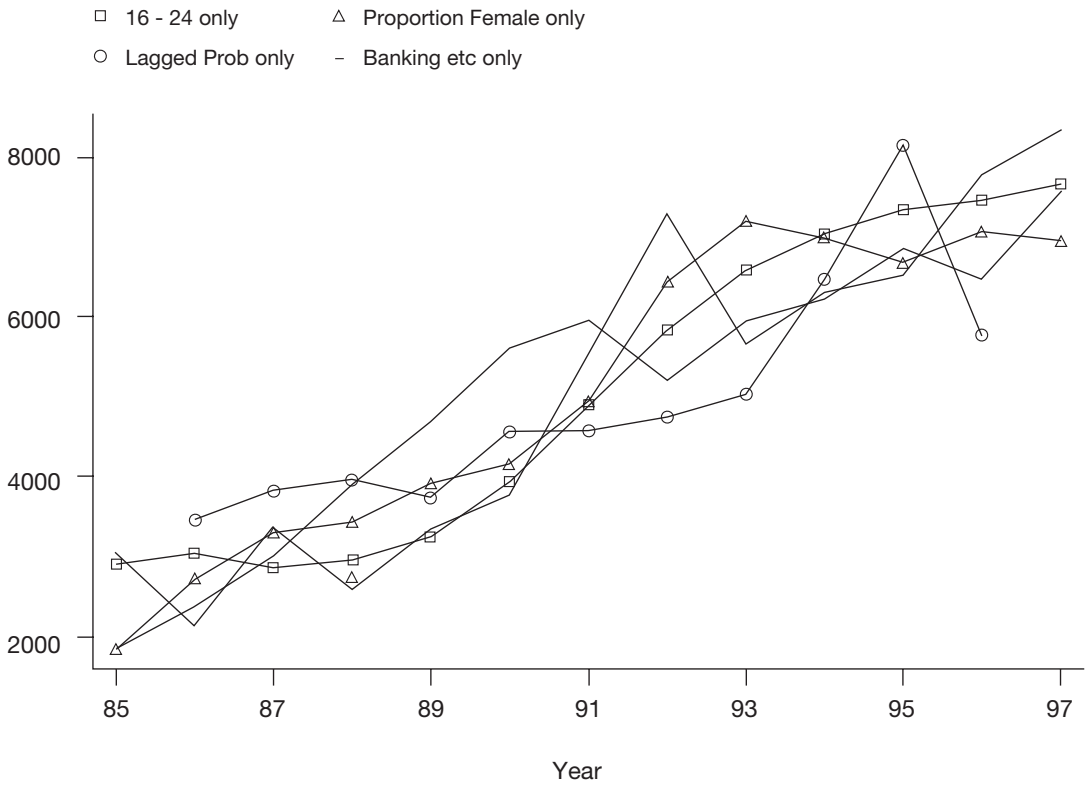
(c) Proportion of labour force aged 16-24

Discrimination applications	*Coefficient*	*Std. Err.*	*t-statistic*
Proportion of labour force aged 16-24	-691.49	77.58	-8.91
Constant	17780.88	1443.71	12.32
Adjusted R^2	0.87		
N	13		

(d) Proportion of labour force in banking and finance

Discrimination applications	*Coefficient*	*Std. Err.*	*t-statistic*
Proportion of labour force in banking and finance	1902.35	367.36	5.18
Constant	-19111.06	4677.90	-4.09
Adjusted R^2	0.86		
N	13		

Figure 15: Fitted and actual values: discrimination cases



c) Wages Act cases

Figure 16 indicates the close relationship between proportion of tribunal success and claims under the Wages Act. The pattern in claims for unlawful deduction from wages clearly follows the probability of winning. There are no data on the median award given under this jurisdiction.[15]

The model estimated was therefore the following:

$$WAG_t = a_1 + a_2\mu_{t-1} + a_4X_t + e_t \qquad (9)$$

where:

- WAG = applications in Wages Act cases,
- μ = probability of winning WAG,
- t indexes the year,
- e = white noise error,
- X = one of the set of either industry, labour force or occupational characteristics that were hypothesised, based on the bivariate analyses and our economic model, to affect the number of cases,
- a = constant,
- $a_2 - a_4$ = coefficients.

Figure 16: Unlawful deduction from wages and proportion of tribunal successes

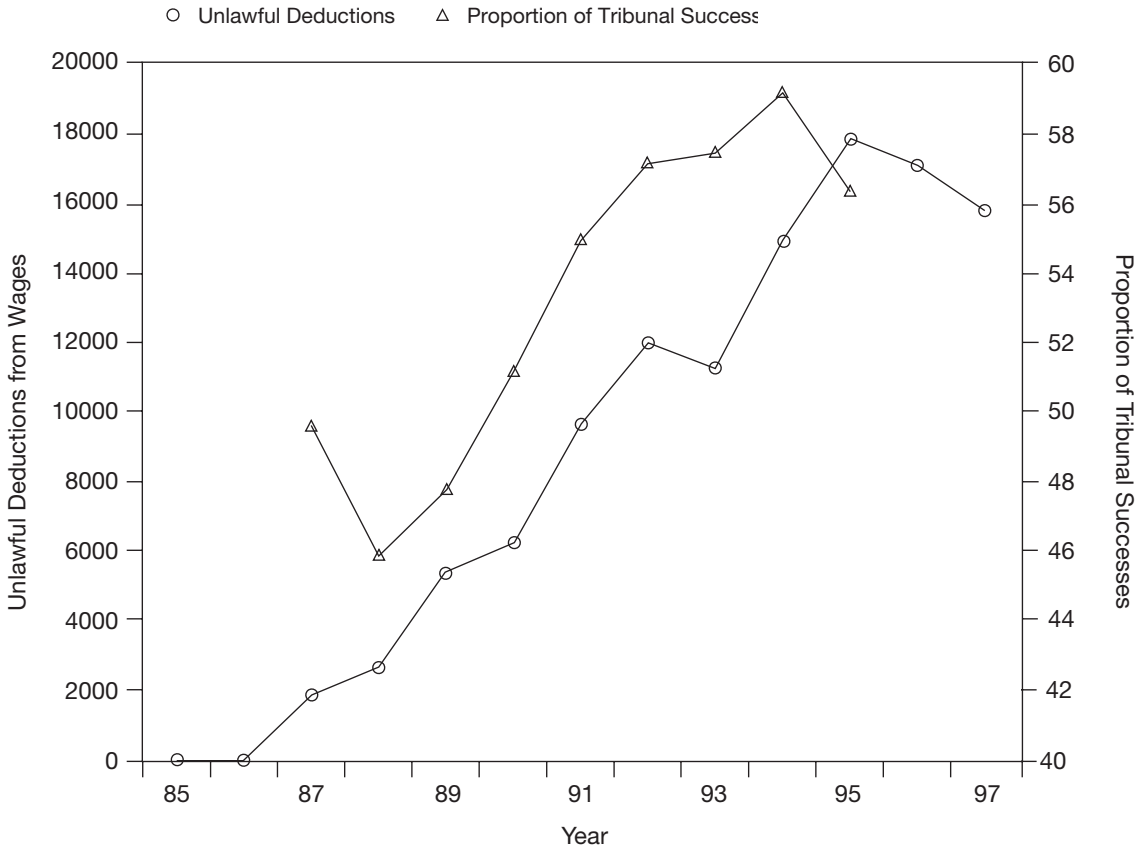


Table 11 reports the t-statistic on each of the estimated parameters where significant, the adjusted R^2 and the number of observations in the regression. It indicates:

- the importance of the (lagged) probability of winning;
- the importance of labour force composition – the proportions of the labour force who are female, part-time, or young are significantly associated with the level of applications;
- that industry structure is sometimes important;
- that it is often difficult to identify a separate significant effect for both the probability of winning and other variables.

On the basis of these results, we select our four models as the preferred models for forecasting unfair dismissals. All models include the lagged probability of winning. The additional explanatory variables are:

- the proportion of employees aged 16-24;
- the proportion of employees in a union;
- the proportion of employees who are employed in banking and finance.

Table 11: Wages Act applications

Variable	*Lagged probability of winning t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	5.0		0.75	9
Trend		3.4	0.95	9
Number of civil cases	4.4		0.71	9
Labour force characteristics (proportion in each category)				
Tenure < 1 year	4.1		0.76	9
Tenure 1-2 years	2.5		0.72	9
Tenure 2-5 years	5.2		0.77	9
Female			0.77	9
Part-time		3.4	0.90	9
Female part-time		1.6	0.79	9
Age 16-24		-4.5	0.93	9
Age 25-49		3.2	0.89	9
Age 50+	2.5	3.5	0.90	9
Union membership	2.1	-6.8	0.97	9
Redundancy rate	5.3		0.79	8
Industry characteristics (proportion of labour force in each category)				
Small and medium size enterprises	2.4		0.72	9
Other services	3.1		0.71	9
Transport	4.4		0.76	9
Manufacturing		-4.4	0.93	9
Banking and finance	2.8	3.0	0.88	9
Distribution	6.5	2.3	0.85	9

The coefficient estimates are given in *Table 12* and the plot of fitted versus actuals in *Figure 17*.

d) Redundancy and Insolvency cases

In the graphical analysis we saw that there appeared to be a correlation between the number of cases in this category and the proportion of employees being made redundant. Below we compute some regressions using this variable as a core explanatory variable.

In line with the rest of the analysis above, we also examine the role of the probability of winning cases. Interestingly, this is highly correlated with the redundancy rate itself (see *Figure 10*). It may be that a recession brings more redundancies and also more people with good cases for applications.

Table 12: Preferred specifications for unlawful deduction from wages

(a) Lagged probability of winning

	Coefficient	*Std. Err.*	*t-statistic*
Lagged probability of winning (all wages act cases)	978.62	197.06	4.97
Constant	-41336.71	10536.02	-3.92
Adjusted R^2	0.74		
N	9		

(b) Lagged probability of winning and proportion of labour force aged 16-24

	Coefficient	*Std. Err.*	*t-statistic*
Lagged probability of winning (all wages act cases)	-315.77	303.25	-1.04
Proportion of labour force aged 16-24	-2568.99	567.32	-4.53
Constant	73359.77	25900.98	2.83
Adjusted R^2	0.93		
N	9		

(c) Lagged probability of winning and proportion of labour force who are union members

	Coefficient	*Std. Err.*	*t-statistic*
Lagged probability of winning (all wages act cases)	263.45	127.56	2.07
Proportion of labour force union members	-1175.20	172.86	6.80
Constant	39187.40	12456.60	3.15
Adjusted R^2	0.97		
N	9		

(d) Lagged probability of winning and proportion of labour force in banking and finance

	Coefficient	*Std. Err.*	*t-statistic*
Lagged probability of winning (all wages act cases)	553.76	195.81	2.83
Proportion of labour force in banking and finance	5795.77	1937.09	2.99
Constant	-94144.82	19065.24	-4.94
Adjusted R^2	0.88		
N	9		

Figure 17: Fitted probabilities for Wages Act (unlawful deductions from wages)

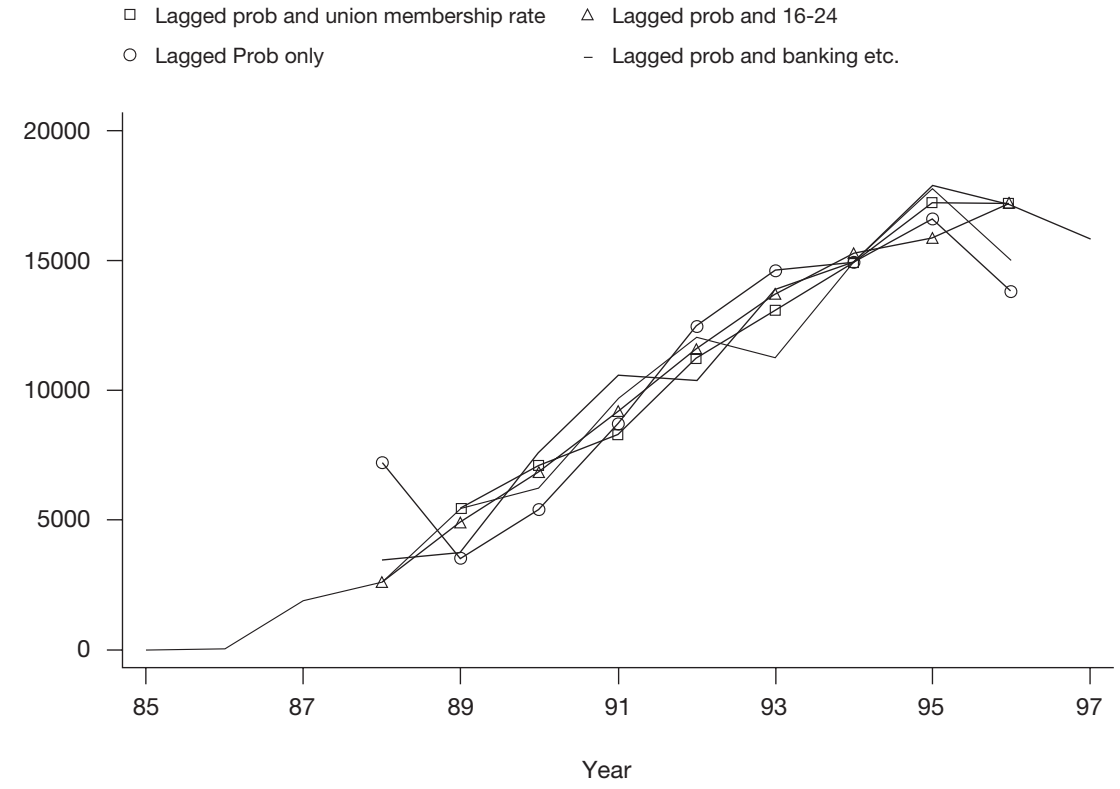
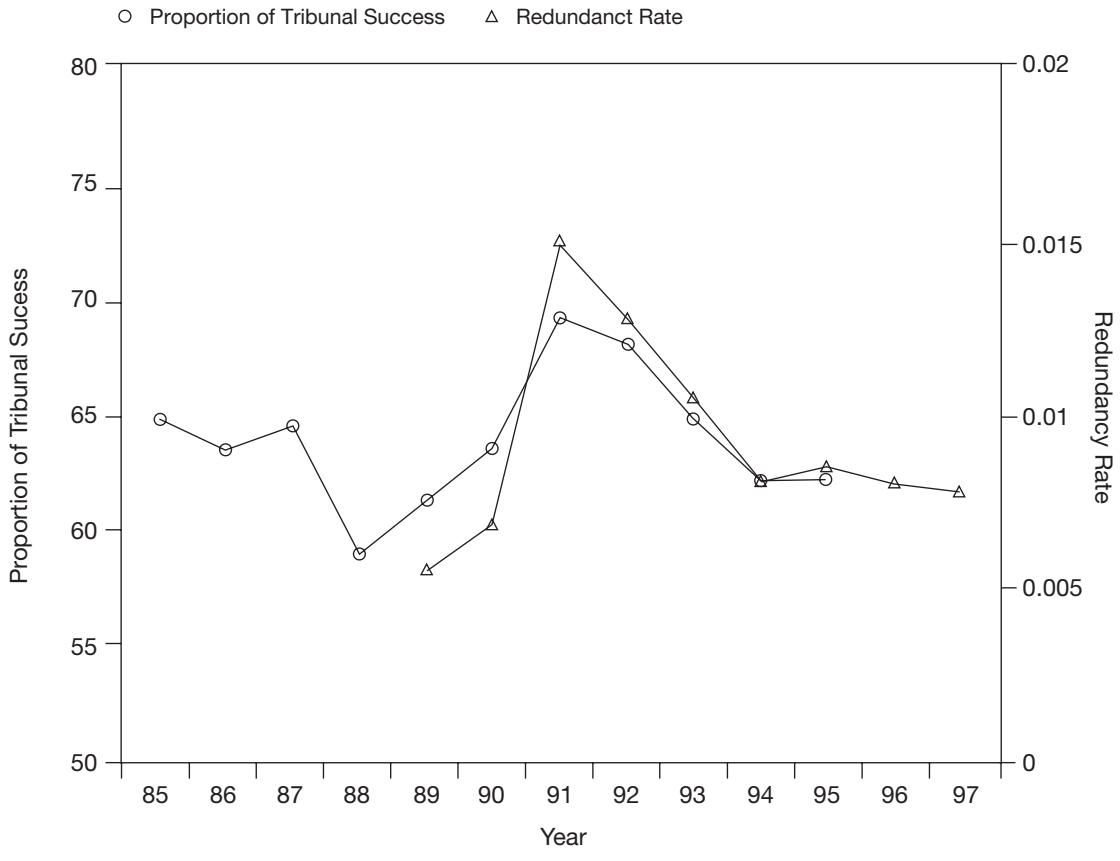


Figure 18: Redundancy rate and the probability of sucess of redundancy applications



We therefore report regressions using the lagged probability of winning. We cannot hope to discriminate between these explanations with the data we have. Both of them significantly raise the number of applications made under this jurisdiction.

$$RED_t = a_1 + a_2\nu_{t-1} + a_4*X_t + e_t \qquad (11)$$

where:

- RED = applications in redundancy and insolvency cases,
- ν = probability of winning redundancy and insolvency cases,
- t indexes the year,
- e = white noise error,
- X = one of the set of either industry, labour force or occupational characteristics that were hypothesised, based on the bivariate analyses and our economic model, to affect the number of cases,
- a = constant,
- $a_2 – a_4$ = coefficients.

Table 13 shows the results of doing this for a selection of variables for X using the hearing win rate, and reports the t-statistic on each of the estimated parameters, the adjusted R^2 and the number of observations in the regression. The table indicates:

- the importance of the (lagged) probability of winning;
- the importance of labour force composition: the proportion of the labour force who are female or in the age group 25-49 are significantly associated with the level of applications;
- industry structure is important – the proportion in small establishments and the declining proportion in manufacturing both matter.

Table 14 gives the preferred specifications.

Table 13: Redundancy and insolvency cases

Variable	*Lagged probability of winning t-stat*	*Variable t-stat*	*Adjusted R^2*	*N*
No other variable	1.8		0.18	11
Trend	2.6	4.0	0.69	11
Number of civil cases			0.22	11
Labour force characteristics (percentages in each category)				
Tenure < 1 year	2.0		0.18	11
Tenure 1-2 years			0.25	11
Tenure 2-5 years			0.25	11
Female		4.5	0.74	11
Part-time	2.1	3.4	0.62	11
Female part-time			0.30	11
Age 16-24	1.9	-4.3	0.72	11
Age 25-49	2.0	4.8	0.76	11
Age 50+			0.08	11
Union membership	3.0		0.99	11
Redundancy rate	1.9		0.56	8
Industry characteristics (percentages)				
Small and medium size enterprises		3.79	0.67	11
Other services		2.0	0.39	11
Transport	3.2	3.1	0.58	11
Manufacturing	2.6	-5.1	0.78	11
Banking and finance	3.9	5.3	0.80	11
Distribution	2.5		0.30	11

Table 14: Preferred specifications for redundancy and insolvency cases

(a) Proportion of workforce in small firms

Redundancy applications	*Coefficient*	*Std. Err.*	*t-statistic*
Redundancy rate	320663.50	150687.70	2.13
% Workforce in small firms	1041.44	277.88	3.75
Constant	-30783.51	8928.19	-3.45
Adjusted R^2	0.80		
N	8		

(b) Proportion of workforce aged 25-49

Redundancy applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probability of winning a redundancy case	332.98	165.65	2.01
% Workforce aged 25-49	875.52	183.67	4.77
Constant	-67873.72	13263.22	-5.12
Adjusted R^2	0.76		
N	11		

(c) Proportion of workforce union members

Redundancy applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probability of winning a redundancy case	510.48	109.45	3.01
% Workforce union members	-466.34	105.60	4.42
Constant	-8818.96	11664.74	0.76
Adjusted R^2	0.60		
N	11		

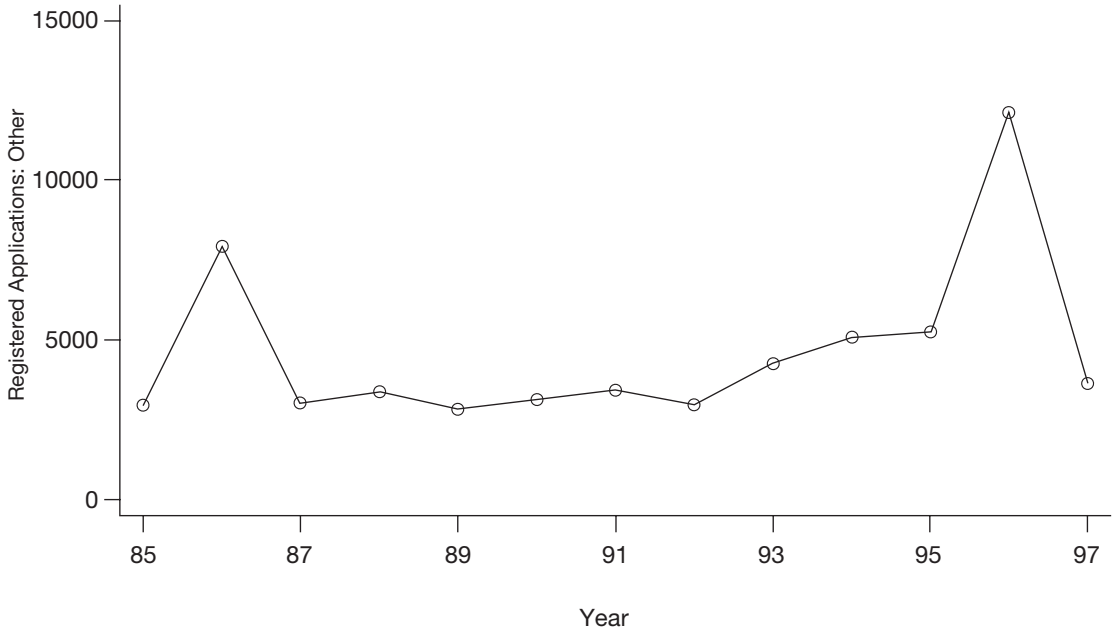
(d) Proportion of workforce in manufacturing

Redundancy applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probability of winning a redundancy case	396.60	155.01	2.56
% Workforce in manufacturing	-1623.78	319.38	-5.08
Constant	17466.35	13222.19	1.32
Adjusted R^2	0.78		
N	11		

e) "Other" Jurisdictions

This category includes all the jurisdictions not accounted for above. Because it is simply a collection of disparate issues, there is no clear direction on the factors that will be important in modelling it. It is clear, however, from *Figure 9* that the series is essentially flat over the 11-year window for which we have data, although it does exhibit two large spikes in 1986 and 1996 for which there are special reasons. Indeed, regressing the series on a time trend yields an insignificant result. This series is untrended and can best be explained simply by its past average value.

Figure 19: Applications under all "other" jurisdictions



4.2 Analysis of Regional Data

Our analysis of regional level data focuses on unfair dismissal cases, discrimination and Wages Act cases. ACAS do not have data on redundancy payments cases and our analysis above concluded that "other" jurisdictions is best considered as flat. The purpose of the regional analysis is:

- to check the robustness of the national analysis, since this is based on very small samples;
- to further investigate the impact of industry and labour force characteristics on the number of cases.

We estimate models using the national probability of winning and the award levels and regional measures of labour force and industrial structure. These underlying drivers for taking a case are as outlined in Chapter 2 above. So applications are based on expected payouts, which are a function of national factors, while the propensity to take action is a function of local labour market factors. We do not use an indicator of litigiousness as this is only available at a national level and was not found to be significant.

Step 1. Graphical analysis

In Section 3.2. we explained how we have adjusted ACAS regional data to give figures that we think are comparable to the ETS national data. *Figures 20 through 24* present these estimates at ACAS regional level. The series are noisier than the national ETS totals and they exhibit considerable regional variation. Total applications (*Figure 20*) rise in all regions, though the rise is not constant across regions. In some regions, notably London, the South East and Yorkshire, there is evidence of a slow-down in growth or even a downturn in total cases at the end of the period.

The pattern in unfair dismissals also differs somewhat by region (*Figure 21*). While all regions except Northern exhibit the rise followed by a fall in growth seen in the aggregate series, the size of the rise and the fall varies somewhat. (The last data point for Northern includes Yorkshire and should be ignored). Discrimination and Wages Act/breach of contract cases rise in all regions through the period, so all regions mirror the national trend *Figure 22 and 23*). The residual category is small, but appears to fall and then rise in most regions.

Figure 20: Total applications by region 1985-95

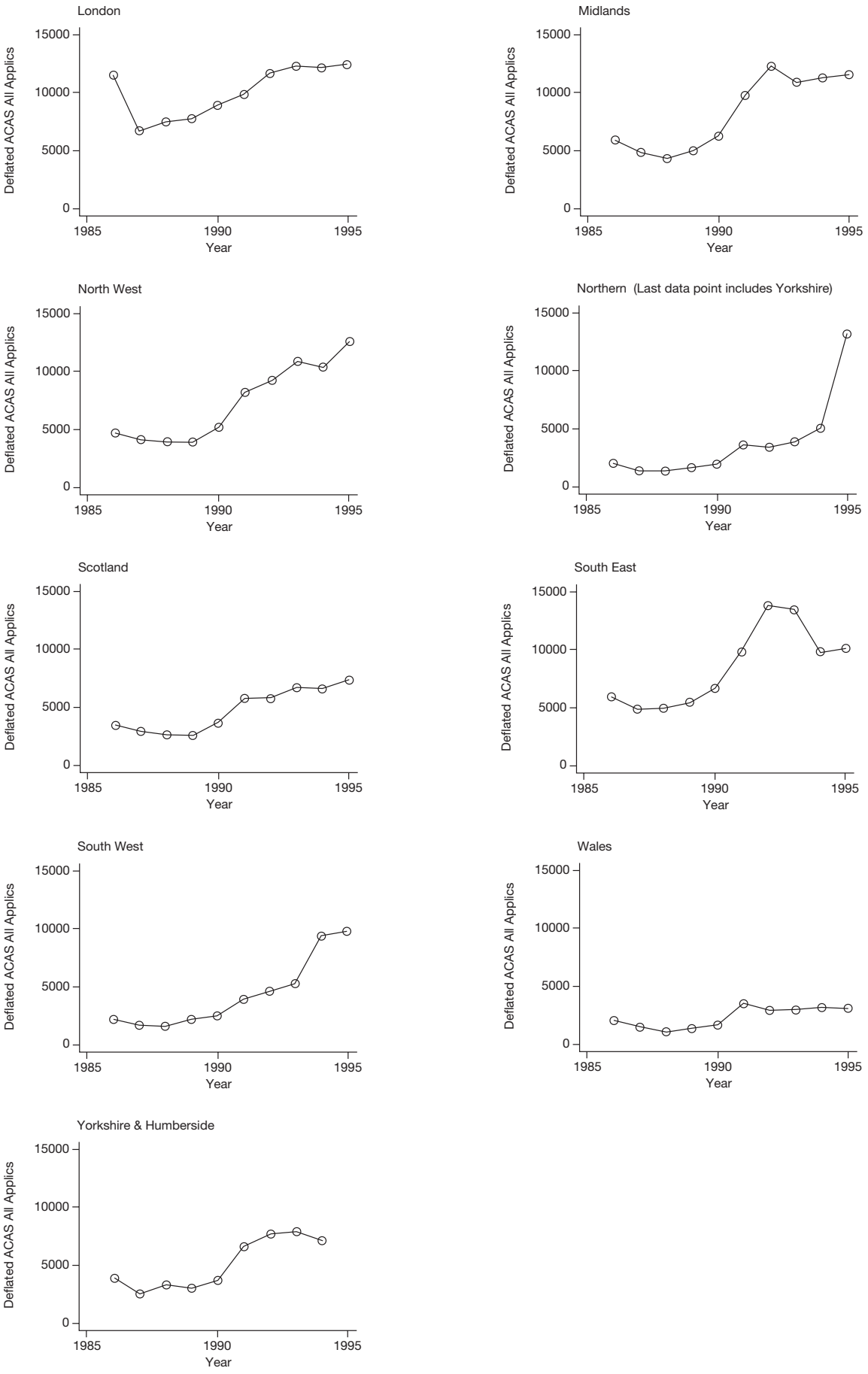


Figure 21: Unfair dismissals by region 1985-96

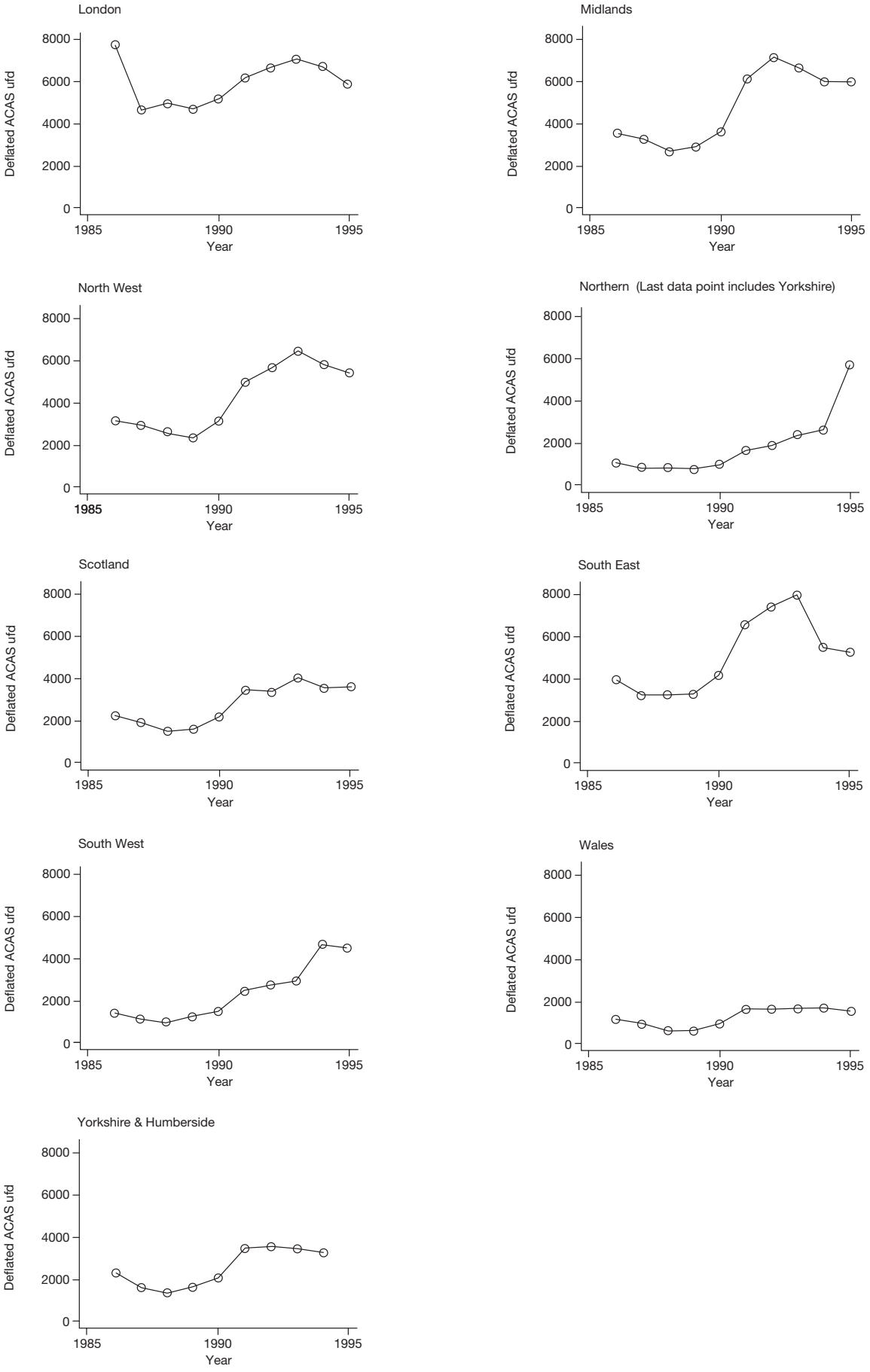


Figure 22: Discrimination cases by region 1985-95

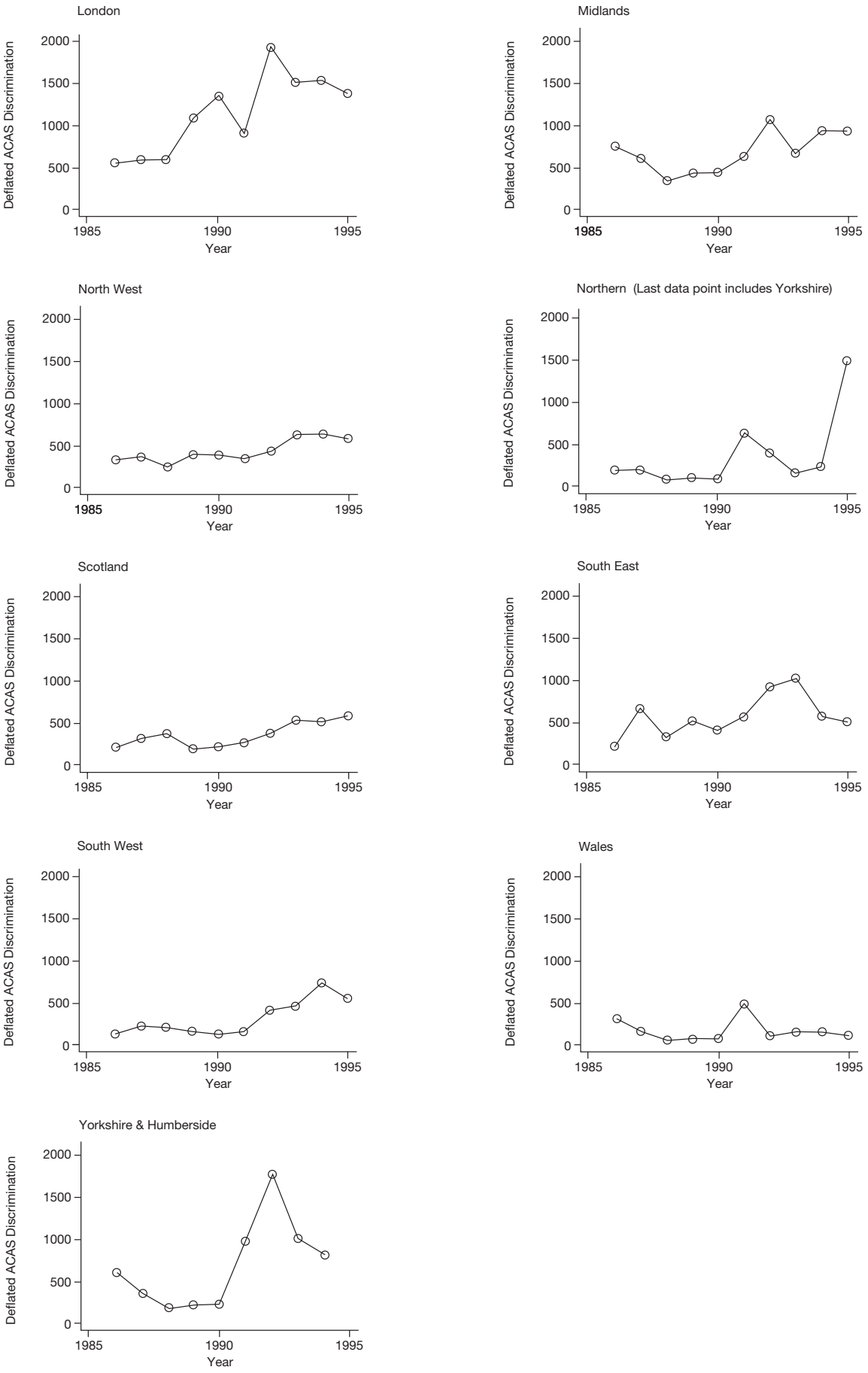


Figure 23: Wages Act/breach of vontract by region

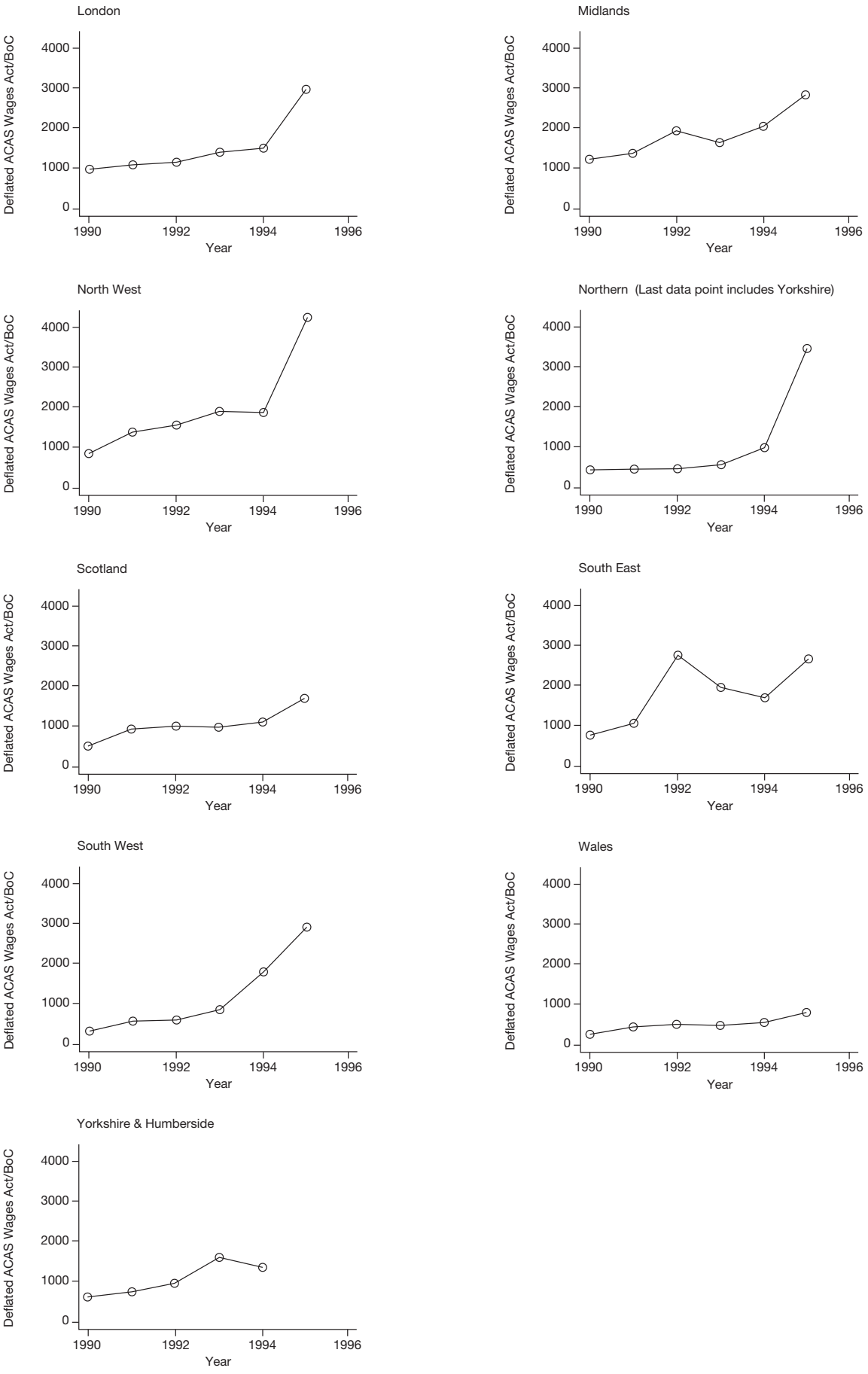
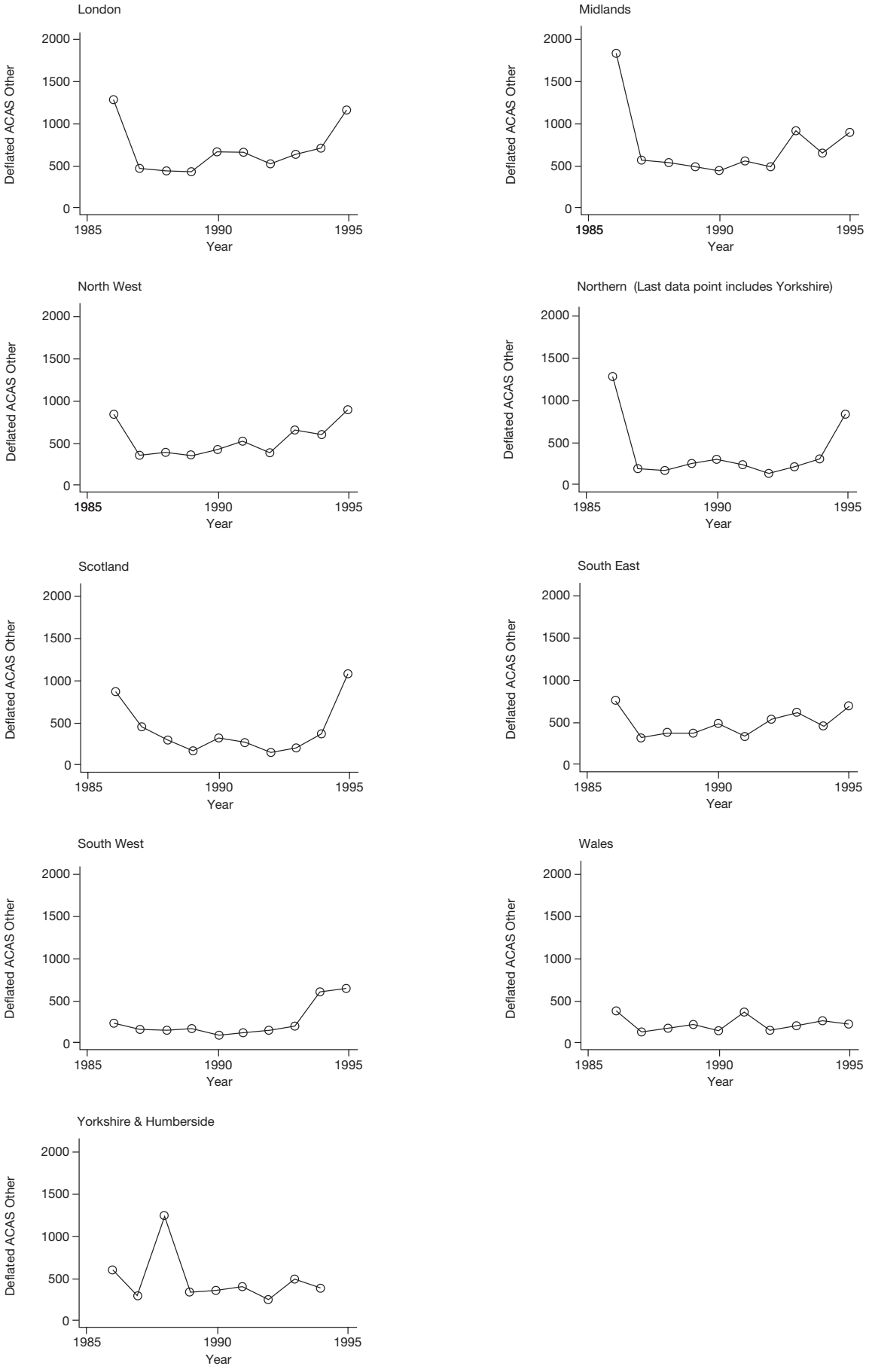


Figure 24: Other cases by region



Step 2. Statistical analysis using one independent variable

Given the larger size of the datasets and the results for the analysis above we do not report the results of Step 2 but move straight onto Steps 3 and 4.

Steps 3 and 4. Multiple regressions and lags

The estimated model for each of these jurisdictions is of the form:

$$A_{jtr} = a_1 + a_2\beta_{jt} + a_3 RMAUFD_{jt} + a_4 X_{tr} + u_{jr} + e_{jtr} \quad (12)$$

where:

- A = application,
- β = probability of winning a case,
- RMA = real median award,
- r indexes the region,
- t indexes time,
- j indexes jurisdictions,
- X_{tr} = a vector of labour force and industrial structure characteristics that are measured at regional level,
- u_{jr} = a vector of regional fixed effects,
- a = constant,
- $a_2 – a_4$ = coefficients.

Identification of the impact of regional parameters in this model depends on the extent of variation in labour force and industry characteristics across regions. *Figure 25* shows that gender and age composition of the labour force vary relatively little across regions. However, *Figure 26* shows that there is more variation in the industry characteristics at regional level. The percentage of the labour force in banking and finance and in distribution, hotels etc., and the unemployment rate varies by region both in levels and, importantly for the purposes of identification, in the pattern of growth.

Figure 25: Selected characteristics of labour force by region

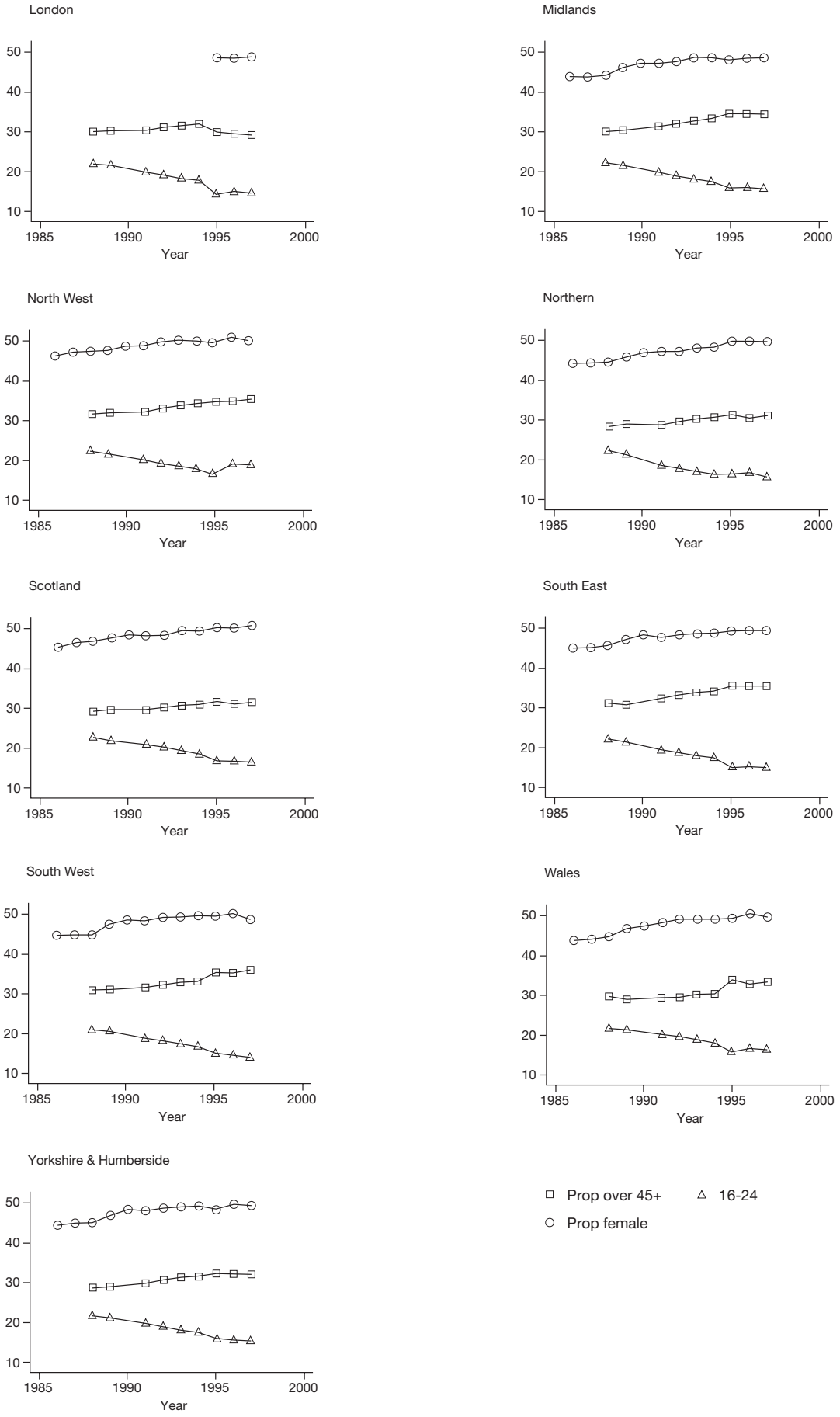
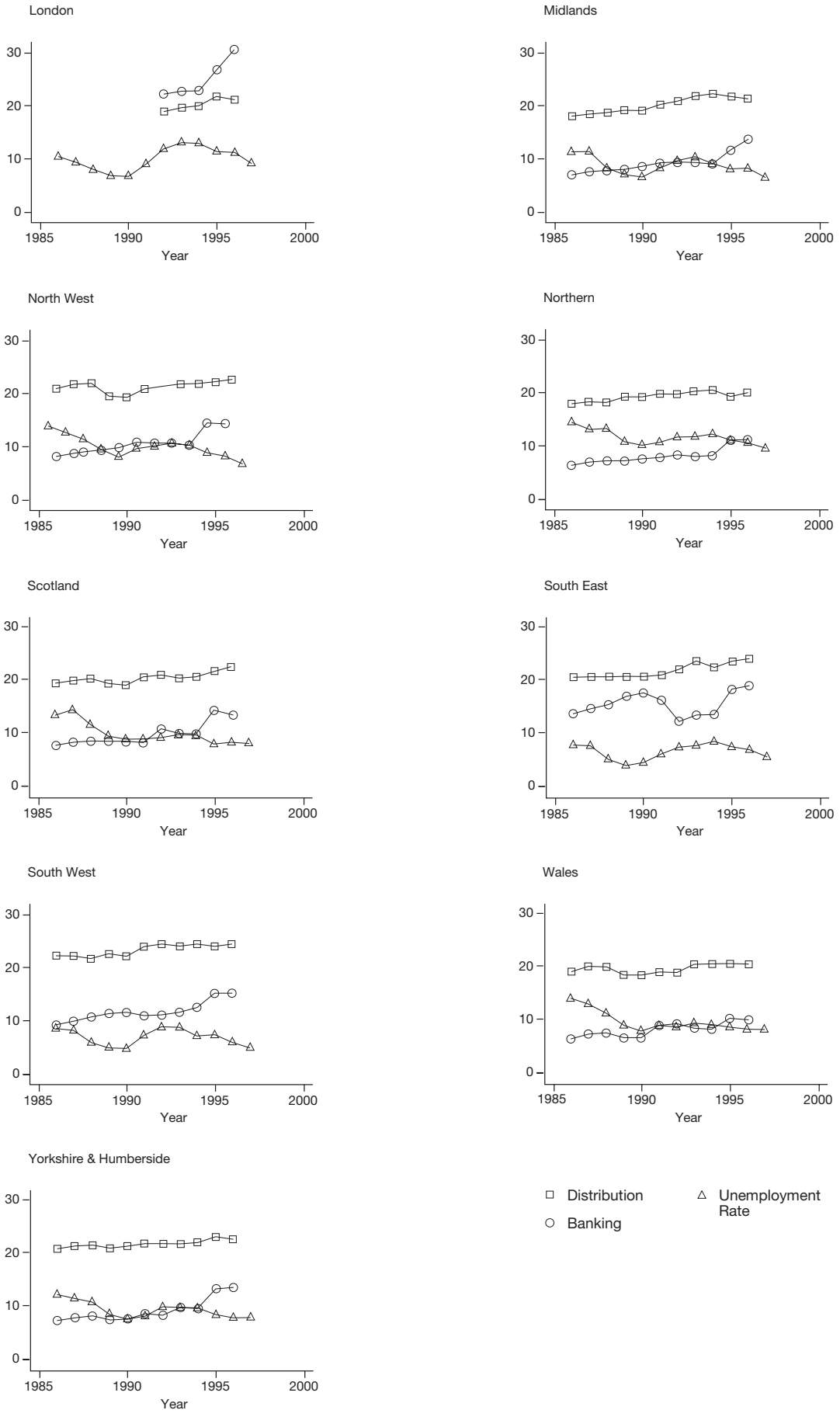


Figure 26: Selected characteristics of industry structure by region



a) Unfair dismissal cases

The results support the analysis of national data.

- Both the probability of winning and a number of labour force and industry characteristics are significantly associated with the number of unfair dismissal cases.
- In most cases, the high correlation between the industry and employee characteristics means that it is impossible to identify the separate effects of these variables when more than one such variable is used in the regression.
- In regressions with the unemployment rate and the number of workers aged 16-24 or the proportion of workers in banking and finance or the proportion of workers in distribution and hotels, it is possible to identify the separate effects of the unemployment rate and the other variables.
- However, the fit of these models is not significantly better than the fit of models with only the lagged probability of winning and one industry or labour force characteristic, so this approach is not investigated further.

The preferred specifications are given in *Table 15* (the model with the percentage of the labour force that is female is included only for comparison with ETS national data analysis). These results confirm the association between age structure of the labour force and the number of claims and between the proportion of the labour force in certain industries and the number of claims. While the coefficient on the probability of winning changes a little between specifications none of these estimates on the probability differ significantly.

Actual and predicted values are given in *Figure 27*.

Table 15: Preferred specifications for regional analysis, unfair dismissal (All models include regional fixed effects)

(a) Probability of winning and proportion of labour force female

Unfair dismissal applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probab. success	103.44	61.89	1.67
Proportion of labour force female	422.88	141.43	2.99
Constant	-20950.97	4971.73	-4.21
Adjusted R^2	0.76		
N	72		

(b) Probability of winning and proportion of labour force aged 16-24

Unfair dismissal applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probab. success	188.04	42.10	4.47
Proportion of labour force aged 16-24	-270.64	67.23	-4.03
Constant	1894.83	2567.07	0.74
Adjusted R^2	0.82		
N	62		

(c) Probability of winning and unemployment rate

Unfair dismissal applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probab. success	270.09	28.56	9.46
Unemployment rate	214.65	63.73	3.37
Constant	-8560.41	1286.74	-6.65
Adjusted R^2	0.80		
N	80		

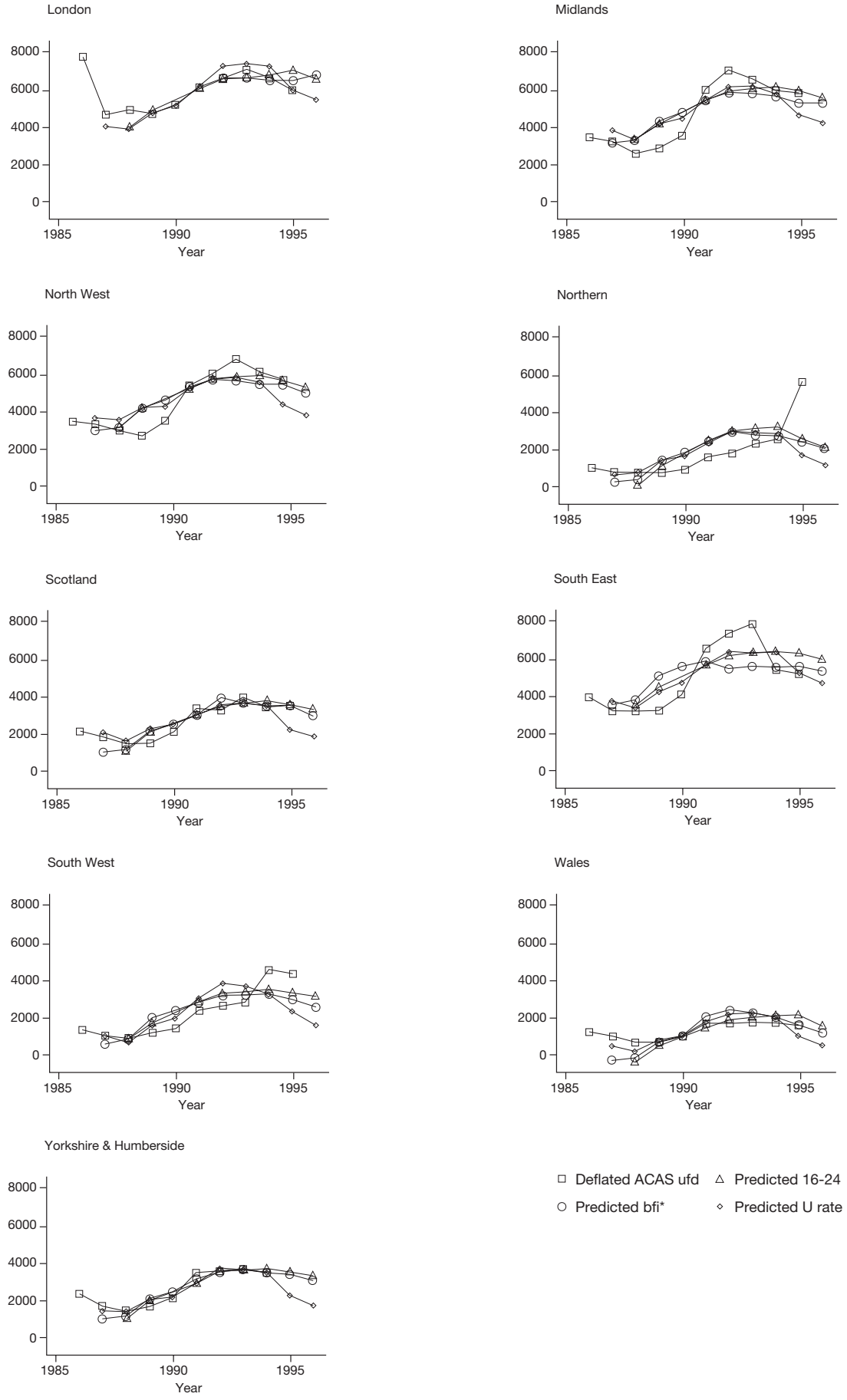
(d) Probability of winning and proportion of labour force in distribution etc.

Unfair dismissal applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probab. success	200.74	31.74	6.32
% labour force in distribution etc.	515.73	114.03	4.52
Constant	-14968.36	2179.73	-6.87
Adjusted R^2	0.82		
N	75		

(e) Probability of winning and proportion of labour force in banking and finance

Unfair dismissal applications	*Coefficient*	*Std. Err.*	*t-statistic*
Lagged probab. success	245.04	32.06	7.64
Proportion labour force in banking and finance	196.19	75.84	2.59
Constant	-7922.46	1314.62	-6.03
Adjusted R^2	0.78		
N	75		

Figure 27: Actual and predicted unfair dismissal rate by region



b) Discrimination cases

The analysis again supports the national data analysis.

- The coefficient of the lagged probability of winning is rarely significant.
- The coefficient of lagged monetary payments for either race or sex discrimination cases is generally significant.
- Coefficients of labour force characteristics (particularly the proportion of the labour force aged 16-24) and some of the industry structure variables (proportion in distribution and hotel, proportion in banking and finance) are significant.
- When more than one variable is entered into the model (on top of the regional dummies) separate effects of the industry, labour force characteristics and the monetary payments cannot be identified.

From this analysis, two preferred models are selected. The independent variable in the first is lagged real median awards (for race cases), and in the second it is the percentage of the labour force aged 16-24. These results are shown in *Table 16*.

c) Wages Act and Breach of Contract cases

In the regional data we analyse not Wage Act cases alone but combine them with breach of contract cases (from 1995). The results nonetheless support the national ETS data analysis:

- The best fitting model includes only the lagged probability of winning.
- Inclusion of both the lagged probability of winning Wages Act cases and industry or labour force structure does not significantly improve the fit of the model.

The preferred model is given in *Table 17* and the plot of actual versus fitted is shown in *Figure 28*.

Table 16:

(a) Regional analysis of discrimination cases: Lagged monetary payouts for race discrimination

Discrimination applications	***Coefficient***	***Std. Err.***	***t-statistic***
Lagged real median award: race	0.20	0.05	4.00
Constant	450.38	119.29	3.78
Adjusted R^2	0.52		
N	80		

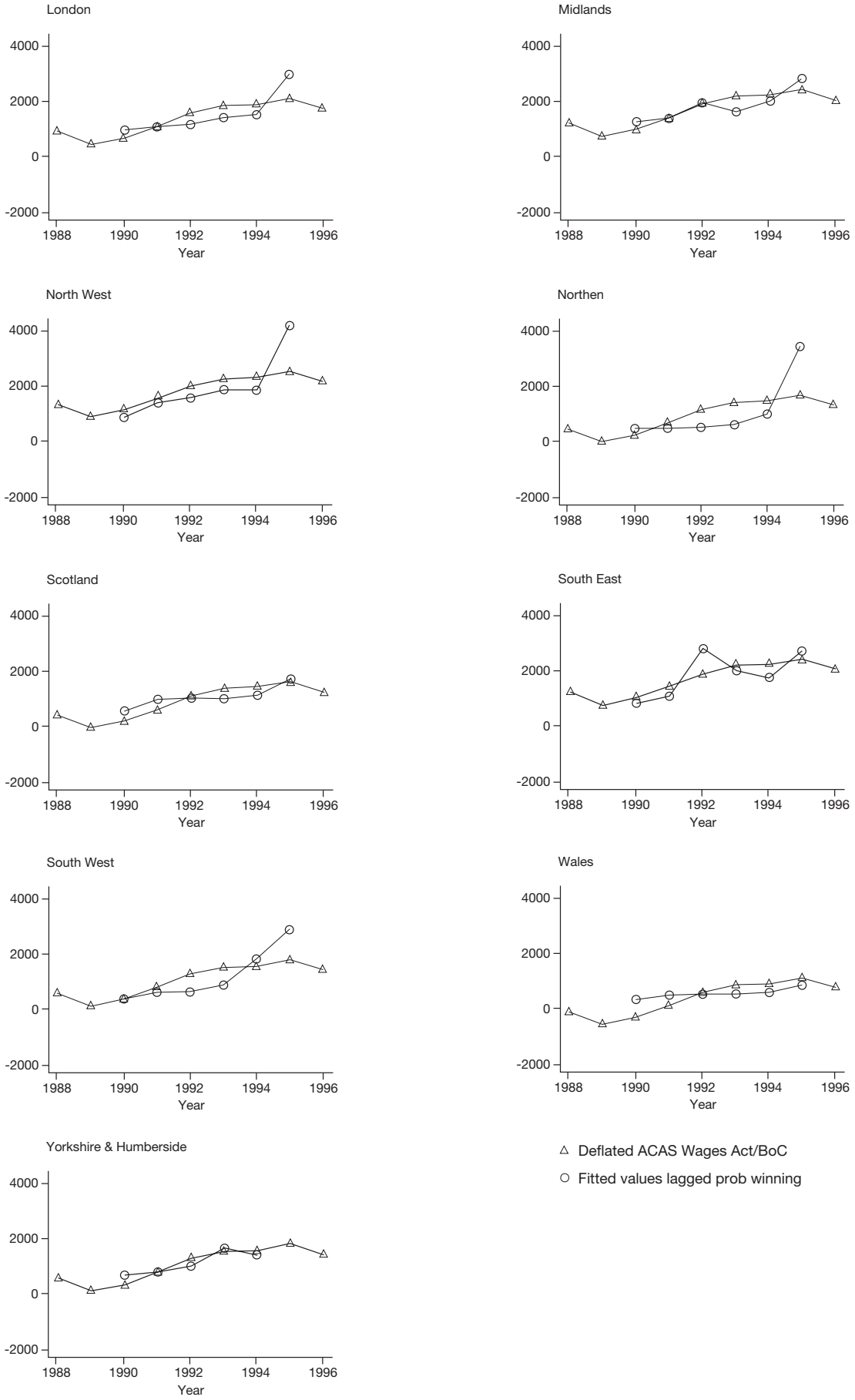
(b) Regional analysis of discrimination cases: Percentage of labour force aged 16-24

Discrimination applications	***Coefficient***	***Std. Err.***	***t-statistic***
Percentage of labour force aged 16-24	-78.39	18.51	-4.24
Constant	2390.62	388.47	6.15
Adjusted R^2	0.55		
N	62		

Table 17: Regional analysis of Wages Act - best fitting model

Wages applications	***Coefficient***	***Std. Err.***	***t-statistic***
Proportion of success (WAG)	126.29	20.62	6.12
Constant	-5667.88	1138.84	-4.98
Adjusted R^2	0.53		
N	53		

Figure 28: Plot of predicted versus actual, regional analysis Wages Act



4.3 Analysis of Long Run Series for Unfair Dismissal cases

This section reports the results of our investigation into the longer run of data available for the Unfair Dismissals jurisdiction. *Figure 18* shows the number of applications and the probability of the applicant being successful. The number of cases grew rapidly after the introduction of the legislation in 1972 to a plateau of around 30,000 cases per year by the late 1970s. It remained at this level until the mid 1980s when it fell to a low of around 18,000 in 1988. Thereafter it rose sharply to top 41,000 in 1993. The figure also shows the success probability – a variable we have shown to be successful in explaining the shorter run of data from 1985/86 to 1995/96. We can see that this story is backed up very strongly by the longer run of data. We see that the success probability rose to a peak of 44% in the mid 1970s just ahead of the peak in the number of cases. The long slow decline in the win rate presages the fall in the number of applications. Finally, as we have seen above, the increase in the success rate since 1986/87 leads the increase in the number of cases. This figure provides powerful evidence of the link between the number of applications made and the lagged win rate.

We now confirm that visual impression with regression analysis. We know, from above, that some trending variable is also required to explain the movements in unfair dismissal cases. In *Table 18* we present the results of regressing the number of applications on the probability of success (lagged one year) and a trend.

The table shows that both the lagged success probability and the trend are highly significant. Note that over this longer run of data the time trend is quantitatively less significant: some 790 cases per year which, compared to a mean level of 30,101, is almost negligible. It is important to be aware that the value of any estimated trend will depend on the period over which it is estimated.

Given the relative luxury of 22 observations we can conduct some diagnostic tests on these results. *Table 19* shows that there is no real evidence of any residual serial correlation or heteroscedasticity. Furthermore, the estimated equation appears to be stable through time. Chow breakpoint tests reveal no evidence of structural breaks either in 1985, about the middle of this sample, nor at 1990 when the sharp increase in the number of applications occurred.

Figure 29: Unfair dismissals and the proportion of cases successful, 1972-1995

Table 18: Unfair dismissal applications regressions
Included observations: 22

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
Constant	-42903.36	11667.83	-3.68	0.00
TREND	787.44	173.29	4.54	0.00
Prob. Success(t-1)	1696.85	286.84	5.92	0.00
R-squared	0.70			
Mean dependent var		30101.68		
Adjusted R-squared	0.66			
S.D. dependent var		8478.45		
S.E. of regression	4918.33			
Akaike info criterion		19.97		
Sum squared resid	4.60E+08			
Schwarz criterion		20.11		
Log likelihood	-216.62			
F-statistic		21.70		
Durbin-Watson stat	1.05			
Prob(F-statistic)		0.00		

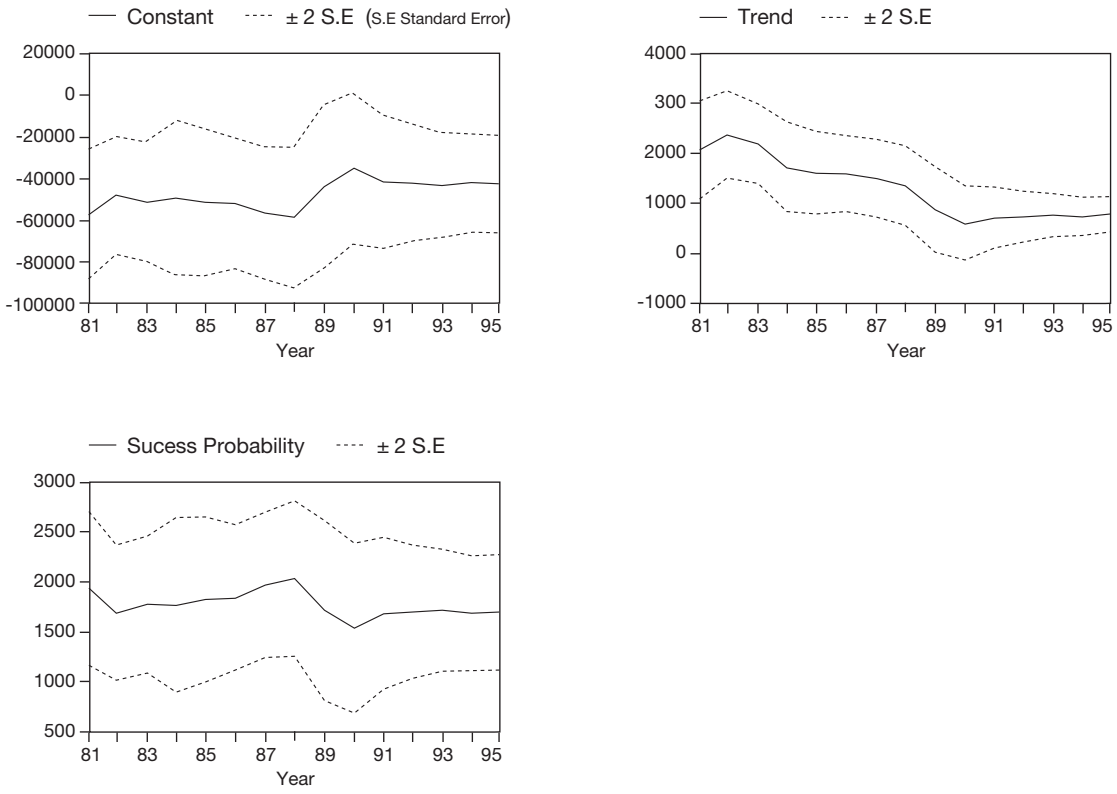
Table 19: Diagnostic tests for Table 18 Estimates

Breusch-Godfrey Serial Correlation LM Test (2 lags):	
F-statistic	2.26
Probability	0.13
Obs*R-squared	4.62
Probability	0.10
White Heteroscedasticity Test:	
F-statistic	2.01
Probability	0.14
Obs*R-squared	7.07
Probability	0.13
Chow Breakpoint Test: 1985	
F-statistic	1.50
Probability	0.25
Log likelihood ratio	5.46
Probability	0.14
Chow Breakpoint Test: 1990	
F-statistic	0.33
Probability	0.81
Log likelihood ratio	1.31
Probability	0.73

A further investigation into parameter stability is presented in *Figure 30*. This shows the result of recursive estimation – estimating the equation over progressively longer windows of data. A good model with stable parameters will show the same value of the estimated parameter whatever window of data is used. This is the case for this model. The coefficient on the lagged probability is remarkably stable. The trend coefficient shows a slight decline over time but this is only to be expected given the nature of a time trend.

In conclusion, this section provides strong supporting evidence of the role of the lagged probability of success in determining applications.

Figure 30: Recursive estimation of coefficients for unfair dismissal model, 1972-1995 data



4.4 Conclusions

To summarise the results, economic variables appear important in explaining the rise in applications to tribunals. The number of unfair dismissal and Wages Act cases is significantly associated with the probability of winning; the number of discrimination cases is significantly associated with the real value of the award made. For all jurisdictions there is also an upward trend in applications that can be measured by either a simple time trend or by changes in labour force and industrial structure that display a general linear trend over the time period. For example, with the general economic recovery in the 1990s, applications did not fall back to the level of the previous recovery.

The statistical analyses therefore support the economic model. The probability of success is significantly associated with the number of unfair dismissal cases, the number of wages act cases and the number of redundancy cases. The number of discrimination cases is significantly associated with the amount of money won.

Industrial structure and labour force composition are associated with the number of cases, and the associations have economic meaning. Thus:

- the rise in number of discrimination cases is closely linked to the rise in the number of women in the labour force;
- the rise in redundancy cases is closely linked to the decline in manufacturing.

The number of unfair dismissals is related to the number of small and medium-sized enterprises, where, perhaps, management structures are such that legislative redress is more often used in the case of a dispute. The decline in union membership and the associated power of the unions, which may rather reflect a move towards more adversarial workplace industrial relations is also closely associated with the rise in several jurisdictions.

The national data analysed in the report cover only a short period (1985 to 1995), due to the lack of records covering a longer time period. This is a problem when many of the factors which would be expected to change results in a change in the level of applications, such as changes in the labour force composition. It is also a problem if these factors change simultaneously or over time. To augment this national data, we examined one tribunal jurisdiction, unfair dismissals, for the longer time period 1972 to 1997 and examined regional level data for 9 regions from 1985 to 1997. Regional data is helpful to the extent that the degree of change in labour force and industry characteristics varies across regions. When we examined the regional data we did not find support for the inclusion of additional explanatory variables. The analysis of the long-term series for unfair dismissal cases

suggested that the results for the relationship with the probability of winning are robust over the longer period.

It is necessary to stress the limitations imposed on the analyses by the data available. As Chapter 3 explained we have encountered several problems that have led to the quantity of data, and hence number of observations, being less comprehensive than was originally planned.

- First, pre-1985 data on applications to tribunals are not available, nor post 1995/96 outcomes data. This reduces the number of annual observations to 11.
- Second, the poor quality of the regional ETS data means we have to use ACAS figures which raises issues of comparability between the national and regional analysis.

End Notes

[11] In the analysis inflation adjusted, i.e. real payments, were used.

[12] From 1989 we use measures of trade union density derived from the Labour Force Survey. For earlier years we have constructed a series derived from trade union membership as recorded in the annual reports of the Certification Officer. This can only be done at a national level, so the earlier years are not included in the analysis of regional data.

[13] The adjusted R2 is a measure of the explanatory power or goodness of fit of a regression relationship. It varies between 0 (no explanatory power) to 1 (a perfect fit).

[14] The t-statistic is a measure of the statistical importance of a variable in a regression relationship. As a rule of thumb, a figure around 2 or higher suggests that the variable does indeed have a role in explaining the movement of the variable of interest.

[15] DTI officials believe they are lower than for other jurisdictions.

Five

FORECASTING THE NUMBER OF APPLICAITONS

The proposed forecasting strategy is as follows.

- In terms of forecasting, the results are based on a small number of observations. But forecasting in terms of economic variables, which may go up as well as down, is preferable to forecasting in terms of a linear time trend. Therefore our preferred forecast equations contain economic rather than trend variables. The trend equations are given in the results section so these may be used instead.
- It is clear that the separate jurisdictions exhibit different patterns. Therefore the preferred forecasting methodology is to forecast separately for the jurisdictions. For unfair dismissal, discrimination, Wages Act excluding breach of contract and redundancy, a preferred forecasting equation based on economic variables is given.
- The methodology for the other two categories is the following. The breaches of contract cases are too new to forecast, so the best forecast is the level last period. The residual category is basically unchanging, so we use the mean over the period.

The chosen equations are:

Unfair Dismissal	=	-131867.5 + 1061.88P(win)(t-1) + 3732.94P(sme)
Discrimination	=	- 66542.87 + 1639.51P(women)
Wages Act	=	39187.4 + 263.45P(win)(t-1) -1175.20P(union)
Redundancy	=	17466.35 + 396.60P(win)(t-1) -1623.78P(mfg)
Other	=	4611.15
Breach of Contract	=	(actual series)

Note:

P(win)(t-1):	the lagged win probability of that particular jurisdiction.
P(sme):	proportion of workers in small and medium-sized enterprises
P(women):	proportion of the workforce who are female
P(union):	proportion of the workforce who are union members
P(mfg):	proportion of the workforce who are in manufacturing

Breach of contract: because we have only three data points we cannot forecast this sub-jurisdiction. For this forecast evaluation exercise, we simply use the actual values. For forecasting purposes, we recommend using the lagged actual value until more data is available for analysis.

To forecast the total we simply add the component forecasts. The result is shown in *Figure 31* alongside the actual total. The fit is reasonably satisfactory. Regressing the actual total series on our forecast yields an R^2 of 0.83 – that is, 83% of the variation is explained. The coefficient on the forecast is 1.071 with a standard error of 0.178. This implies that the coefficient is significantly different from 0 but insignificantly different from 1. Thus, in that sense, it is an unbiased forecast.

In order to use this as a basis on which to forecast, data on the independent variables have to be easily available. Data on the proportions of the labour force in the categories set out above is easily available, and the data on the probability of success is available from the Employment Tribunal Service. So we believe this is a feasible basis on which to forecast.

Figure 31: Actual and forecast total applications