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Profiling benefit claimants in Britain: A feasibility study

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Summary

This study was commissioned by the Department for Work and Pensions (DWP) to explore the potential in using statistical profiling to allocate work-focused interventions within its three main client groups: the sick and disabled, lone parents and JSA clients. Profiling entails the use of statistical models to predict which new claimants are likely to benefit from early treatment, thus assisting in the efficient allocation of resources. Models are run to estimate individuals' probabilities of a relevant outcome – in our case, being out-of-work in a year's time, claiming out-of-work benefits a year after claiming, and the percentage of time claiming out-of-work benefits over a period of 30 months. This probability can be used to allocate treatments (such as intensive caseloading or a job search course) to those thought most likely to benefit.

The focus of this study is to establish how accurately clients can be profiled and the data requirements for accurate profiling. Whether a profiling tool meets acceptable standards of accuracy is a subjective judgement, but we are able to show whether profiling improves on random allocation of treatment – an admittedly low hurdle. We lack information on resource allocation by Personal Advisers which would allow us to compare the performance of profiling with the performance of advisers operating a system which is partly deterministic and partly driven by adviser discretion.

Accurately identifying what is likely to happen to clients in terms of their labour market and benefit claiming prospects is one of two considerations in efficient resource allocation. The second is knowledge of who is likely to benefit most from a particular treatment, and by how much, because efficient resource allocation involves maximising the benefits to treatment net of costs. The differential impact of programmes is beyond the scope of this study, so it is assumed throughout that efficient resource allocation will be best achieved by focusing on those with predicted longer claims which, in turn, assumes the net benefits of treating these claimants are at least as great as the net benefits of focusing on those with predicted shorter spells.

Studies show profiling depends on the quality of data available to predict outcomes. We explore the impact of data richness on profiling accuracy by running alternative model specifications using data from the ONE evaluation. The ONE data and the pros and cons of using it for profiling are discussed in Section 2.1. The most parsimonious models contain the sorts of data that might ordinarily be available to the analyst, whereas fuller models capitalise on the richness of ONE, bringing in data on attitudes and so on, which the Department may wish to collect from clients if it assists in profiling.

We have not sought to identify a 'best' profiling instrument containing only those variables that discriminate across clients in terms of predicted outcomes. This is because the uniqueness of our data and the sensitivity of profiling to business cycle, cohort and real time effects would mean further research would be necessary to translate these models into profiling tools that could be used in the field. Instead, we use a selection of models designed for each of the three client groups to illustrate the sensitivity of profiling to model specification, permitting us to make some general observations about the principles governing profiling.

We also examine how sensitive profiling is to the functional form of the estimator and to other variations in the profiling procedure.

The accuracy of the profiling is determined with a validation sample that is randomly excluded from the estimation sample used to run the profiling model. Diagnostic tests used to determine the accuracy of the profiling model are described in Chapter 2.

Even if profiling is deemed sufficiently accurate it is only a viable option for the Department if it can be implemented successfully in the field. Considerations influencing the practical viability of profiling are discussed in Section 2.2.

Results for the sick and disabled were as follows:

- 70 per cent of the sick and disabled were out of work 12 months after making a claim, and 66 per cent were claiming out-of-work benefits. In the 30 months since claiming, 46 per cent had spent all their time claiming and the mean time spent claiming was 70 per cent.
- Profiling outperforms random allocation of the treatment because the models are good at ranking individuals according to profiled outcomes.
- 'Full' models tend to outperform other models, indicating that there is value to the collection of additional data. However, profiling does not necessarily improve with the addition of further variables.
- The functional form of the model does not make a great deal of difference to profiling accuracy. In the case of out-of-work and benefit status 12 months after claiming, the logit is marginally preferable to the OLS and probit while, in the case of percentage of time spent claiming, the OLS estimator marginally outperforms the tobit.
- The success in targeting the treatment through profiling depends on the proportion of the eligible group to be treated, relative to the proportion who actually go on to be out of work/claim.
- The inclusion of ward-level deprivation data did not improve the accuracy of profiling.
- The exclusion of benefit area dummies makes little difference to the predictive accuracy of the models.
- Models perform differently across sub-groups of clients but all work reasonably well in terms of the profiling diagnostics.
- Confining the analysis to claimants only does not make much difference.
- Altering the size of the estimation versus validation samples does not make much difference.
- The predictive power of profiling models for out-of-work benefit status and out-of-work labour market status is similar.
- Determinants of benefit and out-of-work status 12 months after claiming are similar, but differ in some respects, perhaps suggesting the need to develop alternative models for both outcomes. The determinants of percentage of time claiming over 30 months differ in a number of ways from benefit status at month 12.

- There are no unambiguous advantages to using percentage of time spent claiming rather than benefit status at month 12 as the profiling variable: the relative performance of profiling on these two outcomes, using identical models, differs with the cut-off point chosen to allocate treatment. With a 70 per cent cut-off, the correct prediction rate is higher when using percentage of time spent claiming, but profiling based on wave two benefit status results in slightly better profiling with 30 per cent and 50 per cent cut-offs.

Results for the lone parents were as follows:

- Just over 72 per cent of lone mothers (and 72.5 per cent of all lone parents) were out of work 12 months after approaching DWP to make a claim for out-of-work benefits; 66 per cent of lone mothers (67 per cent of all lone parents) were claiming out-of-work benefits at the 12 month point; 35 per cent of lone mothers spent all of the 30 months since making the claim on out-of-work benefits, the mean percentage of time spent claiming being 67 per cent.

- Profiling outperforms random allocation of the treatment.

- The out-of-work benefit status models perform better than the out-of-work labour market status models because the model generates fewer false negatives.

- Determinants of benefit and out-of-work status are similar but not identical. Determinants of benefit status at the 12 month point and over the 30 month period differ in a number of respects.

- The 'full' models outperform other models when profiling on out-of-work labour market status and benefit status 12 months after claiming but, in the case of the percentage of time claiming over 30 months there are no gains to more extensive models.

- There is little to choose between functional forms but the logit estimator performs marginally better than the OLS and probit estimators when estimating status at the 13 month point, while the OLS outperforms the tobit in estimating time on benefits over the whole 30 months.

- Profiling lone parents with models devised for the sick and disabled produces poorer results than profiling lone parents with models devised specifically for lone parents.

- Models for all lone parents perform a little better than those for lone mothers only.

- Sensitivity analyses made little difference to the results, although there were differences in performance when separate models were estimated for younger and older lone mothers.

- Profiling models for the sick and disabled generally performed better than those for the lone mothers.

Results for JSA clients were as follows:

- In contrast to the other two client groups, only 42.5 per cent of JSA clients were out of work 12 months after making their initial approach to DWP, and 32 per cent were claiming out-of-work benefits at that point. Furthermore, only two per cent had spent all of their time claiming out-of-work benefits over the 30 month period, the mean percentage of time spent claiming being 30 per cent.

- Profiling outperforms random allocation of the treatment.

- The 'full' model outperforms other models in predicting benefit and labour market status 12 months after claiming but, when profiling with the percentage of time claiming over the 30 month period, there are no improvements in correct prediction rates with the fullest models.

- The predictive power of profiling models for out-of-work benefit and labour market status at the 12 month point are similar, though the determinants of these two statuses differ in a number of respects.
- There are no unambiguous advantages to using percentage of time spent claiming rather than benefit status at month 12 as the profiling variable: the relative performance of profiling on these two outcomes using identical models differs with the cut-off point chosen to allocate treatment.
- Once again, the logit marginally outperforms other estimators in profiling status 12 months on, while the OLS performs better than the tobit estimator in predicting percentage of time claiming over the 30 month period.
- Profiling JSA clients with models devised for the sick and disabled produces poorer results than profiling JSA clients with models devised specifically for them.
- In contrast to the sick and disabled, correct prediction rates rise as the target group for treatment narrows. Again, in contrast to the sick and disabled, the correct prediction rate is not particularly sensitive to the cut-off point chosen.
- Irrespective of the cut-off point, negative predictions are less likely to be wrong in the case of JSA clients compared with the sick and disabled, but a higher percentage of those predicted to need treatment actually find a job.
- Irrespective of the cut-off point, out-of-work correct treatment rates are higher for JSA clients than they are for the sick and disabled.
- Sensitivity analyses made little difference to the results, except in the case of the split by gender and age. How well a profiling instrument performs for any of the four sub-groups (men, women, those aged under 35 years and those aged 35 or more) depends on the criterion used to measure accuracy and the model specification.

Taking these results together, we conclude:

- Profiling outperforms the random allocation of treatments but wrong denial and wrong treatment rates are not trivial.
- Whether statistical profiling performs accurately enough for policy purposes is a subjective judgement.
- It would be useful to compare the accuracy rates of statistical profiling with those achieved through PA discretion and the application of deterministic rules.
- The accuracy of profiling turns on the distribution of the outcome variable, the proportion of the client group eligible for treatment, and the variables available to predict the outcome.
- Profiling accuracy rates are at least as good, if not better, for the sick and disabled client group as they are for lone mothers and JSA clients.

1 Introduction

- Government is increasing the assistance offered to new claimants, most notably through work-focused interviews at the beginning of a claim.
- Statistical profiling is one of a number of methods for allocating resources across claimants where it is costly to treat all claimants.
- Under statistical profiling, the statistically assessed probability of a relevant outcome (eg. being a long-term benefit claimant) is used to assign individuals to early treatment.
- The technique is mandatory under federal law in the U.S. for claimants of insurance-based U.I. It is relatively untested in the U.S. and elsewhere and little is known about the accuracy of the technique relative to other resource allocation methods such as adviser discretion and the application of deterministic rules such as the use of benefit durations to determine eligibility for treatment.

This study uses ONE data to profile the Department for Work and Pensions' three main client groups: the sick and disabled, lone parents, and JSA clients. The purpose is to establish how accurately clients can be profiled and the data requirements for accurate profiling, thus informing the design of actual profiling tools which DWP may choose to use in the future. It is not intended to provide a basis for profiling in the field.

1.1 Context

With limited resources and a policy imperative to move claimants off benefits and into work, the Government must determine which method is best suited to the allocation of those resources across clients. In some instances, Governments offer assistance to all within a client group, so there is no need to ration help. For instance, the New Deal for Lone Parents is available to all lone parents and basic JSA job search help is available to all JSA clients from the beginning of a claim. However, the need for a mechanism to allocate resources increases with the cost of the intervention. Traditionally, this allocation has occurred through one of two mechanisms. Treatment has been either offered or withheld on the basis of Personal Adviser[1] discretion, or else treatment is offered in a deterministic way according to client characteristics. In the latter case, a salient characteristic has been the time the individual has remained on benefit. Knowing that many claimants will leave benefit of their own accord, or with little assistance, in the early period of their claim, it may seem sensible to target

[1] Personal Adviser is the current job title for caseworkers in Jobcentre Plus.

intensive intervention on those who have remained on benefit for a period – often six months. This can help tackle the problem of deadweight wherein government unnecessarily devotes resources to helping clients who, in fact, required little or no help. The difficulty with this approach is two-fold. First, those who are perhaps in a seriously disadvantaged position at the outset, whose probability of going onto longer-term benefit receipt was high at the outset, receive fewer resources than one would ideally like to offer them. Second, longer-term benefit claiming has its own negative impact on individuals' subsequent probabilities of leaving benefit for work, a problem which is particularly acute in Britain (Machin and Manning, 1999).

Recently, Government has increased the assistance offered to new claimants, most notably through work-focused interviews at the beginning of a claim.[2] This offers Personal Advisers the opportunity to discuss job prospects with those entering the system, identifying barriers to work and individuals' aspirations. It means Personal Advisers have the opportunity to assess individuals' probabilities of (re-)employment at an early stage. But these early interventions, offered to all, can be costly. This has raised interest in the possibility of using statistical methods to best allocate resources. This method of resource allocation, known as statistical profiling, has been pioneered in the United States, where it has been used primarily to assess the probability that an individual will exhaust their six months' entitlement to Unemployment Insurance. The statistically-assessed probability is used to determine whether or not that individual will be assigned to early treatment on, for example, mandatory training.

As part of the Incapacity Benefits Reform Pilots starting in October 2003 (proposed in the 'Pathways to Work' Green Paper published in November 2002), the Department for Work and Pensions (DWP) will be increasing the early assistance given to those beginning a claim for Incapacity Benefits. In these pilots, profiling will be used to help direct limited resources more effectively. The profiling will be conducted by Personal Advisers at the first work-focused interview (eight weeks after the start of the claim) to all claimants (except those exempt from a Personal Capability Assessment, i.e. those with severe disabilities). The Personal Advisers will input the data into a web-based tool that will put the claimants into one of two groups. Those predicted to return to work quickly will be screened out and not be required to attend more work-focused meetings (though they may choose to attend on a voluntary basis). The group predicted not to return to work quickly will be screened in and required to attend the additional work-focused meetings.

Profiling remains controversial (OECD, 1999) and earlier efforts in Britain have met with limited success (Payne et al., 1996; Employment Service, 1996; Wells, 1998). Profiling depends critically on the quality of data available to predict outcomes (see Section 2.2.3). Advances in the collection of survey and administrative data, exemplified in the ONE evaluation that provides the data for this profiling exercise, should offer good opportunities for improving on past efforts. However, this study is more ambitious than previous studies since efforts have been made to profile all three major client

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[2] Work-focused interviews have been a feature of many welfare-to-work initiatives since ONE. ONE was a pilot service launched in June 1999 that sought to help people claimants overcome obstacles to paid work. It required all new clients to consider their capacity to work and their position with respect to the labour market prior to receiving benefit. In October 2001, the Jobcentre Plus Pathfinder offices were introduced ahead of a national roll-out programme. Jobcentre Plus aims to improve the delivery of the work-focused interview (WFI) regime piloted in ONE. Since April 2001, lone parents already in receipt of Income Support were invited to attend a mandatory Personal Adviser meeting on a phased basis, starting with lone parents whose youngest child was between 13-15 years of age and gradually working down through the age groups. From April 2003 the last extension was made to new and repeat claimants whose youngest child is aged between 0 and 3 years.

groups – the sick and disabled, lone parents and the unemployed. British research has focused largely on the claimant unemployed and, as noted above, profiling in the United States has been used to target resources among claimants to time-limited Unemployment Insurance, as opposed to the lone parents who make up most U.S. welfare recipients. Thus, this study breaks new ground in profiling lone parents and the sick and disabled in Britain.

1.2 Scope

This study was commissioned by the DWP to explore the potential in using statistical profiling to allocate work-focused interventions within its three main client groups: the sick and disabled, lone parents and JSA clients.

Profiling entails the use of statistical models to predict which new claimants are likely to benefit from early treatment, thus assisting in the efficient allocation of resources. In this study, models are run to estimate individuals' probabilities of being out of work a year after claiming, claiming out-of-work benefits a year after claiming, and the percentage of time claiming out-of-work benefits over a period of 30 months. In the 'real world' these probabilities might be used to allocate treatments to those thought most likely to benefit. However, this study is a theoretical exercise to establish how accurately clients can be profiled and the data requirements for accurate profiling, thus informing the design of actual profiling tools which DWP may choose to use in the future. It is not intended to provide a basis for profiling in the field.

Whether a profiling tool meets acceptable standards of accuracy is a subjective judgement, but we are able to show whether profiling improves on random allocation of treatment – an admittedly low hurdle. We lack information on resource allocation by Personal Advisers which would allow us to compare the performance of profiling with the performance of advisers operating a system which is partly deterministic and partly driven by adviser discretion.

Government may seek to achieve various social goals through the allocation of resources across benefit client groups. It may be that the primary goal is allocation of services equitably – serving those most in need. Alternatively, the aim may be the efficient allocation of services, that is, serving those with the largest net benefits from participation. Or else, the policy may be attempting to fulfil both objectives at once. The broad policy aims are important since they determine which profiling variable or variables are optimal (see Section 2.2.1).

If efficient resource allocation is a key aim, one faces an important difficulty. To know what constitutes efficient resource allocation, one must know how individuals respond to treatment. In a world where one assumes homogeneous treatment effects (such that all are likely to benefit equally from treatment, or more intensive treatment), and marginal costs are homogeneous then there is no efficiency gain from serving those with longer expected claims. For example, if half of the claims will last 10 weeks and half 20, but all claims are reduced by two weeks at some constant cost if treated, then there is no efficiency gain to concentrating treatment on those with expected durations of 20 weeks. However, where a treatment works equally well regardless of an individual's characteristics, substitution effects may be minimised where resources are targeted on those least able to compete in the open market, offering a rationale for focusing on those with predicted longer-term benefit spells. It is possible that treatment effects will be heterogeneous, in which case efficient resource allocation dictates that treatment should be given to those with the largest net benefits from participation. *A priori*, it is not possible to tell whether net benefits will be greater for those with predicted longer benefit claims or those with predicted shorter benefit claims. (It is even plausible that, if those with predicted shorter benefit spells benefit disproportionately from the sort of treatment currently on offer, their propensity to leave benefits more quickly than anticipated may itself represent a treatment effect rather than deadweight.)

Whether the caseloading approach or other treatments imply homogeneous or heterogeneous effects is beyond the scope of this study.[3] We simply assume that efficient resource allocation will be best achieved by devoting resources to those with predicted longer-term claiming. This implies that the net benefits of treating these clients will be at least as great as the net benefits of focusing on those with predicted shorter spells.[4] In future, research needs to be undertaken to establish the nature of treatment effects since targeting those with the potential for longer claims is only efficient if these types of client respond to treatment.[5]

A related issue is the need to distinguish between the effectiveness of profiling, on the one hand, and the effectiveness of the treatment being profiled, on the other. As Black, Berger and Smith (2001: 3-4) put it: 'A profiling system (or any other system of assignment to services) might do a good job of allocating an ineffective service or it might do a bad job of allocating an effective service'. In this study, we are concerned solely with the performance of profiling in ranking clients according to subsequent benefit outcomes. The study does not address the effectiveness of the caseloading approach to servicing new clients.

1.3 The experience of profiling

Statistical profiling was pioneered in the United States. Since the mid-1990s statistical profiling has been mandatory under federal law for all U.S. states allocating resources to claimants of time-limited Unemployment Insurance under the Worker Profiling and Reemployment Services (WPRS). UI recipients are entitled to up to six months' benefit, depending on their contributions record, after which time all benefits cease, unless they qualify for means-tested assistance under Temporary Assistance for Needy Families (TANF). Profiling identifies which claimants will be likely to exhaust UI and targets available job search assistance according to the ranking of their probability of exhaustion. The literature evaluating the performance of UI profiling identifies important lessons for profiling in Britain:

- In the U.S., profiling generally performs poorly in ranking UI recipients according to their subsequent benefit experiences. Successful profiling depends critically on the quality of data available to predict outcomes (see Section 2.2.3). Profiling in Kentucky is more successful than elsewhere due to the rich set of covariates entering the model (Black, Berger and Smith, 2001; Black *et al.*, 2003).[6]

[3] ONE was an important development of the caseloading approach in Britain. However, ONE has been superseded by Jobcentre Plus which adopts a similar caseloading approach to servicing clients.

[4] In turn, this assumes that welfare losses are at least as great among individuals experiencing longer claiming spells, a contention that needs empirical validation since, in theory, it is not necessarily the case (Black, Berger and Smith, 2001).

[5] The feasibility of such research relies on impact and cost data being available.

[6] The Kentucky model contains over 140 covariates, whereas the original Worker Profiling and Reemployment Services model consisted of five covariates. Elsewhere, Pennsylvania uses only eight covariates and Washington State uses 26 (Black *et al.*, 2003). Black *et al.* (2003) take data for Kentucky and identify a 'best specification' that balances predictive performance and simplicity. It contains 17 variables: education, single digit occupation, tenure with last employer and tenure squared, type of shift working patterns, UI benefit exhaustion in the previous year, an indicator of previous UI benefit claims, welfare transfer payments made, food stamp receipt, public transport for getting to work, eligibility for the JTPA programme, quarterly wages in the last year, whether enrolled in school at the time of claiming, and whether employed at the time of claim.

- Variance in the outcome variable can improve the predictive power of estimates.
- There is no evidence from the profiling of UI claimants in Kentucky that those claimants with longer expected unemployment durations have larger treatment effects (Black *et al.*, 2003). Indeed, in spite of good profiling relative to most states, it seems the efficiency goal is not being obtained (Black, Berger and Smith, 2001).
- Profiling models should be regularly updated to take account of changes in their predictive power arising from changes such as business cycle effects.

In interpreting the profiling evidence for the U.S., it is important to recall the differences between the U.S. and British contexts. First, whereas in the U.S. case, attention is focused on predicting exhaustion of short-term benefit entitlements, in the British case benefits are not generally time-limited. Second, services available to UI recipients are typically short term and inexpensive compared with longer-term training programmes offered to welfare recipients, and individuals can often enrol in most services without referral. Thus 'the predictive power of the model is not as critical as it would be if the statistical model were used to refer individuals to longer-term and more expensive services, and if the model precluded individuals with lower assigned probabilities from using services' (Eberts and O'Leary, 1997). This may explain why there is no profiling for the majority of welfare recipients in the U.S., who tend to be lone mothers with longer-term benefit entitlements and eligibility for more expensive welfare-to-work programmes.[7] Just how profiling might be used to allocate which type of resources is yet to be seen in Britain.

Canada and Australia also use statistical methods for the early identification of those most likely to have long unemployment spells but, unlike in the U.S. where Personal Adviser discretion is explicitly prohibited in the allocation of reemployment services to UI recipients, these countries allow Personal Advisers discretion to override the formal model to refer clients. Some other countries, like the Netherlands, rely solely on Personal Adviser judgement to identify those at risk of long-term claiming (see Eberts and O'Leary, 1997 for a review).

Profiling remains controversial (OECD, 1999), especially in Britain where earlier efforts at profiling have met with limited success (Payne *et al.*, 1996; Employment Service, 1996; Wells, 1998). Payne *et al.* (1996) used the National Child Development Survey to predict unemployment at age 33 years. Their job was made difficult by the fairly small sample sizes available and the low incidence of unemployment (nine per cent). The authors express concern at the error rate in their ability to predict unemployment accurately, and suggest further research on larger data sets covering the full age range and a wider set of covariates. The Early Identification Pilot, run in seven Employment Service Jobcentres in 1994, came to similar conclusions in trying to predict claim durations and the probability of unemployment 12 months in to a claim.

As noted above, successful profiling depends critically on the quality of data available to predict outcomes. This study uses data from the ONE evaluation, which exemplifies advances in the collection of survey and administrative data. This offers good opportunities for improving on past efforts. However, this study is a little more ambitious than previous studies since, for the first time, it profiles the sick and disabled, and lone parents, as well as the unemployed who have been the exclusive focus in previous studies.

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[7] The first field experiment assessing the value of profiling for welfare recipients was conducted in Michigan in 1998/1999 (Eberts, 2002).

The remainder of the paper is set out as follows. Chapter 2 explains the methods used in this study: it introduces the data and discusses data issues when profiling; explains the rationale behind model building and the choice of outcome variables; and describes the procedures adopted in profiling clients and diagnosing the effectiveness of profiling. Chapters 3, 4 and 5 present analysis and results for the sick and disabled clients, lone parents and the unemployed respectively. Chapter 6 concludes by summarising the results and identifying practical implications of the study and further issues that could be addressed in establishing what value there might be in profiling DWP clients.

2 Method

- The study uses data generated by the evaluation of ONE in 24 areas of Britain. Individuals approached DWP about claiming out-of-work benefits in the spring and summer of 2000.
- Three profiling outcomes were chosen, namely whether out of work 12 months after approaching DWP about a claim, whether claiming an out-of-work benefit 12 months after the claim, and the percentage of time spent claiming out-of-work benefits between the initial approach to DWP and 31 December 2002.
- The accuracy of the profiling is determined with a validation sample that is randomly excluded from the estimation sample used to run the profiling model.
- Two methods are used to estimate the accuracy of profiling. First, the validation sample is ranked according to predicted outcomes, and differences in the means of these outcomes are calculated for quintiles of the predicted outcomes. Second, cut-off points are chosen to simulate a resource allocation rule, determining who receives treatment and who does not. Using the cut-off to determine the 'correct' observed state of the individual, we calculate the percentage of claimants who had their outcomes correctly predicted; the percentage who were falsely predicted to be in need of assistance ('false positives'); and the percentage falsely predicted as not needing assistance ('false negatives'). Models are compared using these criteria.
- We test the sensitivity of profiling accuracy to model specification, the profiling outcome variable used, the functional form of the equation, the adoption of different cut-off points, the inclusion of individuals who failed to make a successful initial claim, and to sub-groups within each client group.

The technical feasibility of statistical profiling depends on the production of a predictive tool that meets acceptable standards of accuracy. The great danger with profiling is that it fails to identify with sufficient accuracy the people who go on to be long-term claimants, who may have merited more assistance at the outset, producing a high proportion of what are often termed 'false negatives', or that it predicts longer-term claiming for people who, in the event, move off benefit relatively quickly (the 'false positives' which generate deadweight). This chapter addresses the methodological, data and analytical issues arising through statistical profiling with ONE data. There is no single definition of 'accuracy' in the literature: section 2.3 outlines the criteria we use to measure accuracy in this study.

2.1 The ONE data

The data used in this study are taken from the ONE database originally produced to evaluate the impact of The ONE pilots (see Green *et al.*, 2003). The full data set consists of 14,572 individuals who approached DWP to make claims for out-of-work benefits in June/July 2000. The data cover three client groups – the sick and disabled, lone parents and the unemployed. Individuals are eligible for ONE when making a new claim for one of the following benefits: Jobseeker's Allowance (JSA); Income Support (IS); Incapacity Benefit (IB); Invalid Care Allowance (ICA); Severe Disablement Allowance (SDA); Widows Benefit (WB); and Bereavement Benefit (BB). Eligibility for ONE is triggered by new claims for these benefits, including transfers across benefits and approaches about claiming which might not, in the event, result in a successful claim.

The evaluation was conducted in 24 areas – 12 pilot areas running three variants on the ONE treatment (namely the 'basic' model, the 'call centre' model, and the private/voluntary sector model) and 12 comparison areas, each pilot variant being matched to four comparison areas. Individuals were sampled for the survey using the Labour Market System (LMS), with the exception of lone parents and the sick and disabled in the comparison areas, who were sampled from the GMS benefit system. Unlike the LMS, one is supposed to have made a successful claim for benefit to enter GMS. Face-to-face interviews were conducted with survey participants in autumn 2000 – four to five months after ONE entry – and again in April – June 2001, that is, nearly a year after ONE entry. We have matched in data on all benefit spells for the period 1 July 1999 – 31 December 2002.

The ONE evaluation is confined to those survey respondents who said they had successfully established a claim for benefit (Green, Connolly, Marsh and Payne, 2003). However, there are three reasons why it seems appropriate to profile the whole sample, regardless of whether they went on to claim:

- First, in the real world, when an individual approaches DWP staff about a new claim, the Personal Adviser does not know who will go on to establish a claim successfully and will need to assess the priority attached to serving that individual at the earliest opportunity.
- Second, respondent recall regarding their claimant status may be unreliable.[8]
- Third, failure to establish a claim may be a ONE treatment effect where staff 'divert' individuals before claiming, in which case it seems wrong to ignore this group of clients. Therefore, we profile the whole sample, but we test the sensitivity of results to the exclusion of those who said they did not claim.

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8 Although anyone approaching DWP to claim benefit was eligible for ONE in the ONE areas, the control group samples of sick and disabled and lone parents were drawn from the GMS, a claimants-only data base. (Coverage of the unemployed in the Labour Market System (LMS), which does identify people making an approach for a claim, means the unemployed control sample should include some who were non-claimants at the time of ONE entry.) Despite this, many of the control group members said in the survey that they had not made claims around the time they would have been eligible for ONE, indicating some inaccuracy in self-reported claiming. In the case of the sick and disabled, for example, 147 control group clients said they had not claimed.

There are four advantages in using the ONE data for profiling:

- First, the data are very rich in covariates, increasing the chances of accurately profiling individuals.
- Second, the sample sizes are quite large, offering the prospect of reasonable precision in estimation and offering the opportunity to consider sub-group analysis.
- Third, as noted above, we are able to match the data to administrative information on benefit records. This is valuable because:
  - these data do not suffer from recall error or sample attrition;
  - there is greater variance in the outcomes derived from the benefit data than there is in the outcomes derived from the survey data, a factor which, as the U.S. literature indicates, contributes to more accurate prediction.
- Fourth, these are the only recent data available for all three client groups in Britain.

However, there are some limitations in relying exclusively on ONE data that should be noted when interpreting the results and in considering extensions of this research:

- First, there is the difficulty in replicating the models elsewhere since data will be absent for other cohorts who have not been surveyed in this way.
- Second, profiling is concerned with the prediction of benefit and labour market outcomes. It would be an error to load variables into a profiling model with a view to maximising the model's statistical power if the set of variables included those which are merely associated with the outcome of interest, rather than predictive of it. In the case of the ONE data, this raises questions about the use of attitudinal data, which was collected at the first wave interview – some four to five months after ONE eligibility – since these attitudes may themselves be the outcome of the early experience of benefit claiming. Unless one can identify good theoretical grounds for arguing that attitudes are *persistent* over time, and thus not subject to change as a result of the experience of claiming, they ought not to be used to predict outcomes. We have chosen to test the sensitivity of prediction to the inclusion and exclusion of attitudinal data to illustrate what might be gained by the early collection of attitudinal data from DWP clients.[9]
- Third, following on from this point, if one adopts a purist approach and wishes to exclude wave one data as predictors, there is comparatively little in the survey to estimate early exits from benefit.
- Fourth, the ONE data are time-specific. In any subsequent research, it might be worthwhile considering the use of data sets from different time periods to get at real time and business cycle effects, and cohort effects arising from changes in the eligible population over time. These might include Restart data, matched to data on the subsequent 12 years or so on benefit claiming.

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[9] This problem of causation regarding attitudinal data collected post-claim is familiar to most evaluators. It is the reason why NDLP evaluators sought to obtain attitude data prior to treatment from lone parents. See White and Kileen (2000) for sensitivity of their results on adult career advice to the inclusion and exclusion of attitude data, and their discussion of theoretical reasons for the persistence or otherwise of attitudes.

- This might help overcome a fifth problem: the recency of the ONE data means one cannot profile to identify longer-term benefit outcomes. We have addressed this issue in so far as we can by matching in administrative benefit data for the period through to December 2002, the latest date for which full data are available.

- Sixth, the ONE data span the period during which ONE changed from a voluntary to a compulsory programme, and there is the possibility that the ONE pilot created exceptional circumstances which might not hold for subsequent entry cohorts.

- Seventh, the data are drawn from pilot and treatment areas – they are not nationally representative – so it is difficult to extrapolate from these results to the population as a whole. Finally, the data are subject to sample attrition and survey non-response. In an effort to overcome this, all analyses are weighted with weights that are the inverse of the probability of sample selection multiplied by the probability of survey response (see Green *et al.*, 2003, Appendix A for details of the weighting schema).

2.2 Considerations in model building for profiling

This section considers the issues informing the construction of models which try to predict accurately the benefit and labour market outcomes of sick and disabled clients eligible for ONE.

2.2.1 Selection of outcome variables

The choice of variable whose predicted value will determine the allocation of services is key to determining the effectiveness of profiling. As noted by Black, Berger and Smith (2001:9) 'the optimal profiling variable is the one that maximises the attainment of the goals of the allocation mechanism'. If we assume the goal is efficiency, the optimal profiling variable is the one whose allocation of the programme maximises the total net impact of the programme. This is not clear *a priori*. Time to job entry may be optimal, but only if those leaving for jobs do not return to benefit after short periods of time (that is, 'churning' must be relatively low). Time spent claiming may prove the optimal profiling variable, but only if claimants do not leave to claim other benefits beyond the social security system, or create other costs (eg. through crime).

We have chosen three outcomes:

- whether out-of-work at the wave two interview, roughly four to five months after claiming;

- whether in receipt of any ONE out-of-work benefits at wave two, roughly a year after claiming;

- the percentage of time spent claiming any out-of-work benefits between the date of ONE eligibility and 31 December 2002, which is the last date for which we have complete benefit data.

The first two outcomes are measured about a year after ONE eligibility. The key distinction in terms of labour market status is that between those doing some paid work and those who do not. Although highly correlated with whether claiming an out-of-work benefit, the correlation is not perfect and the determinants of benefit status are likely to differ in some ways from those of labour market status. Consequently we profile for both outcomes. Although the same outcomes are available at wave one, that is, four to five months after ONE eligibility, we have not profiled on those outcomes because many of the independent variables used in the profiling are collected at the same point in time, making causal inference difficult. The advantage of using the status measures one year on is that it permits clearer interpretation of the causal relationship between independent variables, most of which are collected at wave one, and outcomes. By counting time spent on all the major out-of-work benefits it overcomes measurement error associated with receipt of only one benefit.

There is one overriding technical consideration that must inform the choice of outcome variables, namely the ability to predict accurately the outcome with available data. Profiling is often dogged by bunching in the distribution of the dependent variable. If there is little variation in the variable to be predicted, then successful prediction is easy for the modal outcome, but not particularly useful. In these circumstances, statistical profiling can often produce many false negatives because even those with estimated lower probabilities of longer-term claiming are found on benefit. Bunching is a feature of the U.S. literature for the profiling of UI recipients since, typically, around four-in-ten claimants exhaust their six month entitlement. In our case, the bunching is similar in the case of the unemployed, with roughly five-in-ten remaining jobless 12 months later and four-in-ten remaining on out-of-work benefits. But it is even more severe in the case of the sick and disabled and lone parents where, in both cases, around seven-in-ten remain jobless and seven-in-ten remain on out-of-work benefits. Our third outcome – the percentage of time spent claiming out-of-work benefits between ONE entitlement and the end of December 2002 – helps overcome this problem by increasing the variance in outcomes. It has five further advantages. First, it is not subject to recall error and so avoids measurement error that might affect survey responses. Second, the data are not subject to sample attrition, a potential source of bias for the survey measures collected at wave two. Third, by counting time spent on all the major out-of-work benefits it overcomes measurement error associated with movement between different out-of-work benefits. Fourth, the measure effectively adds together the effects of exits from and re-entry to benefit, thus overcoming any false inferences that might be made on the basis of first exits from benefit. (In fact, we know churning is a feature of the data, with many respondents having a number of benefit spells). Finally, the outcome is more long-term than status one year on, thus giving a more reliable picture of what the long-term prognosis is for the individual.

2.2.2 Functional form of the regression equation

The precise regression techniques required depend on the nature of the dependent variables chosen as the basis for profiling. Whether out of work 12 months after their claim for benefit, and whether in receipt of any out-of-work benefits 12 months after their claim for benefit are both (0,1) outcomes amenable to modelling using logit or probit models. However, research in the U.S. suggests that the predictive performance of profiling models with (0,1) outcomes is best when using a linear estimation model (Black, Smith, Plesca and Shannon, 2003). Where the outcome is continuous, but there is severe bunching in the upper or lower part of the distribution, the standard regression procedure is the tobit. But, again, U.S. research indicates that the OLS performs at least as well as the tobit, if not better, with such outcomes (Black *et al*, 2003; Black, Berger and Smith, 2001). This does not mean that the OLS will suffice in the case of ONE clients. We therefore follow Black *et al.* (2003) and Berger *et al.* (2000) in testing the sensitivity of our results to alternative functional forms – specifically logit, probit and OLS in the case of our first two outcomes, and OLS and tobit for our third outcome.

2.2.3 Independent variables used to predict outcomes

Evidence from the United States indicates that data quality and the set of covariates used to predict benefit duration is critical in determining the effectiveness of profiling (Black, Berger and Smith, 2001). In particular, the Kentucky profiling approach more accurately predicts UI exhaustion because the model contains more relevant covariates than the models used in most other states in the United States. In many modelling situations there are good grounds for parsimonious specifications – for example, when model construction is grounded in sound theory and geared to the testing of clear alternative theoretical propositions. However, in the case of profiling, omitted variables can lead to seriously biased estimates of individuals' subsequent benefit experiences. Fuller models can also discriminate more across individuals since, where models contain only a small number of variables, there are fewer potential values of the fitted probability. Furthermore, non-significant variables in this case may prove significant predictors for other client groups, or in changed circumstances (see below for further discussion). At the same time, as noted earlier, it is vital that the model serves the purpose of *predicting* benefit outcomes, rather than simply accounting for variance in a descriptive sense. With this in mind, we have devised three model specifications: a parsimonious model containing variables which are likely to be exogenous; a 'middling' model containing an additional set of covariates likely to be exogenous; and a 'full' specification which contains some variables which may be endogenous with respect to labour market and benefit outcomes. These three models differ across client groups, so they are presented in the sections on analysis and results.

We have not sought to identify a 'best' profiling instrument containing only those variables that discriminate across clients in terms of predicted outcomes. Even if we had wanted to do this, the uniqueness of the ONE data and the sensitivity of profiling to business cycle, cohort and real time effects would mean further research would be necessary to translate our ONE models into profiling tools that could be used in the field (see Section 2.2.4 for further discussion). Rather, we use the parsimonious, middling and full models to illustrate the sensitivity of profiling to model specification, permitting us to make some general observations about the principles governing profiling. An understanding of the way profiling operates also benefits from the presentation of similar models across client groups and outcomes. Although our models differ across client groups to enhance their predictive power for each group – often resulting in the exclusion of variables that do not enhance predictive power – where a variable adds to a model's predictive power the variable is usually entered in a similar way across models to permit comparisons of the variable's impact across client groups and, within client groups, across outcomes. This is so even if a variable could be configured more parsimoniously in some cases, while retaining its predictive power. This is not the procedure one would adopt in constructing the 'best' profiling instrument for a particular outcome or particular client group.

The work done in the preliminary phase of this project (Cockerham, 2002), coupled with the work undertaken by Joan Payne (reported in Chapter 5 of Green *et al.*, 2003) gave clear indications as to the variables that predict benefit durations and benefit exits for the three client groups in this data set. The literature on the unemployed emphasises the importance of pre-claim work histories (time in paid work, time since last paid work, pre-claim earnings, patterns of benefit claiming). In the absence of administrative information on the pre-claim period, we rely on retrospective data taken at the wave one interview to construct a two-year work and benefit history.[10]

It is also conceivable that the area a client lives in will affect individuals' ability to leave benefit for paid work. Administrative data on benefit stocks and flows in the Travel-to-Work Areas (TTWAs) covered in the survey help identify local labour market conditions in the period prior to individuals' eligibility for

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[10] Although, as we show later, these variables perform well in the profiling, future profiling might benefit from administrative data on benefit claiming prior to the current claim going back some way. Respondent recall, particularly regarding the distinction between claimant and non-claimant spells of non-work, can be prone to error. If this error is systematic with respect to variables also associated with post-claim benefit durations, predictions of benefit claiming may be biased. The administrative data would provide a check on the recall data taken from the respondent. If it goes back further than two years, it might provide more information on benefit histories which would be useful in predicting benefit outcomes post-claim.

ONE. We have also mapped in ward-level information on seven dimensions of deprivation, namely:

- income deprivation;
- employment deprivation;
- health deprivation and disability;
- education, skills and training deprivation;
- housing deprivation;
- geographical access to services;
- child poverty.

In addition, we use a multiple deprivation index based on the first six items listed above. The motivation for this is the possibility that individuals' prospects are determined not only by their own attributes and local labour market conditions, but the constraints imposed on individuals by their physical and environmental surroundings. Local deprivation is likely to determine, at least in part, individuals' local opportunities for employment and training, the degree of social exclusion individuals experience, and the problems individuals face in other spheres of their life. These ward-level indices are only available for England, so when we test the sensitivity of results to the inclusion of ward-level deprivation we lose from the analysis cases in the two Scottish benefit areas (Clyde and Tayside) and the Welsh pilot area (South East Gwent). The indices are for 2000, but the measures on which they are based relate to 1998 – 1999. We identified the ward the clients lived in when they became eligible for ONE and matched in the deprivation indices for that ward.[11] The degree of client clustering within wards is quite low because the 24 benefit areas used in the ONE evaluation are large: there are usually only one or two clients per ward.

One also needs to bear in mind that the ONE data are pilot data testing the impact of ONE, with some claimants entering the treatment, others not. If the treatment has an independent effect on claimant outcomes, this needs to be accounted for in predicting individual outcomes. We do this in two ways. First, we incorporate six dummy variables distinguishing pilot and comparison areas for each of the three ONE models (basic, call centre, and private/voluntary). Then we replace this six-way categorisation with 24 dummies identifying each of the 12 pilot and 12 comparison areas. Although, in our case, these benefit area dummies also account for any ONE effects associated with the evaluation, these 24 area dummies are the closest variables we have to benefit office sites which are often used in profiling U.I. clients in the U.S.. A profiling scheme treating an equal percentage at each site could not make use of this variation in predictive power associated with site variables in determining which clients to treat, so we consider how well the models perform when benefit area dummies are excluded.

All the other variables are taken from the wave one interview. Those in our most parsimonious and 'middling' models such as age, gender, qualifications, marital status, number of children, and characteristics of the pre-ONE job, will not be affected by the experience of benefit claiming and so can be used in predicting benefit outcomes post eligibility for ONE. However, our fullest models include variables that may well have been affected by benefit claiming. They include attitudes towards paid work, discussed earlier, subjective measures of health (general health, mental disability, long-standing illness), the perceived impact of care responsibilities on opportunities for paid work,

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[11] See *Indices of Deprivation 2000*, DETR Regeneration Research Summary Number 31 for full information on these indices and their derivation.

access to a car and telephone, and possession of a driving licence. The number of other household workers is also included in this category, since household labour supply is often the result of decisions made jointly by household members. The purpose of including them in the analysis is to test the sensitivity of results to their inclusion. If we assume, for the sake of argument, that these variables are unaffected by the experience of benefit claiming, these models indicate what might be achievable if this sort of information was collected at the beginning of a claim.

One can, of course, think of variables that might be highly predictive of benefit outcomes that are not contained in the data. For instance, the Personal Adviser's assessment of the individual's likely time on benefit, assessed at the beginning of the claim, can be a very powerful predictor of subsequent outcomes, as research conducted in Switzerland indicates (Gerfin, Lechner and Steiger, 2001).[12] Nevertheless, the models presented below contain many of the variables one would expect to see in analyses of labour market outcomes for these groups of DWP clients.

2.2.4 The utility of models produced

This research is assessing models that are accurate at predicting benefit outcomes. But the utility of the models to the DWP and to Jobcentre Plus depend on two critical factors: the use to which they will be put in the field and the need to replicate the models.

The predictive tool may be passed to Personal Advisers in the front line who, having collected the relevant data, will be expected to convert it into statistical predictions of benefit outcomes, thus informing resource allocation. If so, the data must be easily collected or available through administrative data. Alternatively, statistical predictions may be undertaken by staff in central offices – either at regional, district or even national level – or else by academics contracting with the Department, as often happens in the WPRS in the United States. 'Remote' profilers may have access to administratively held data, but information from the Personal Adviser initial interview might have to be transmitted to them in a readily-analysable way. If insufficient investments are made in developing accurate and timely methods of data collection on a wide range of variables, the profiling system may be compromised by predictions based on insufficient or inaccurate data. The replicability of the predictive tool is also important because what predicts accurately for one group, or in one location, or at a particular time in the business cycle, may prove less effective as a predictor in another context. Thus, Black *et al.* (2003) find the predictive performance of their profiling models varied substantially with unemployment levels and suggest occasional re-estimation may improve the performance of profiling models. Models based on ONE data may produce accurate predictions but, if these data are not available for most clients most of the time, it is questionable just how valuable these predictive tools will be. The challenge for the Department is to generate the necessary data so that all clients can be profiled over time. This has proved very demanding in the United States, which explains why so many statistical profiling systems rely on a small set of covariates, producing inefficient resource allocation. The assumption in this study is that the data used in these models could be obtained through the administrative system (LMS and/or GMS) combined with information collected at the first new claim interview using a form akin to that originally devised for Restart interviews.

Although there are many practical advantages to parsimonious models, one potential disadvantage

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[12] Bell and Orr (2002) also provide evidence that caseworkers are good at predicting outcome levels (even conditional on clients' characteristics) but very bad at predicting impacts.

might be the ability of Personal Advisers and claimants to seek to manipulate results to produce predictions which serve the purposes of the adviser or claimant, potentially undermining efforts to achieve the best allocation of resources.

Another consideration in model building is the extent to which policy makers and Personal Advisers must be able to make intuitive sense of the predictive model. This might suggest a model that is, in large part, driven by theoretical considerations. That is to say, models might focus on those individual and local features which, in theory, one would expect to predict outcomes. However, in the course of exploration, the analyst may uncover variables that, despite playing a minor or insignificant role theoretically, actually have empirical power in the predictive model. These factors may not be directly interpretable, but they may, nevertheless, enhance the predictive capacity of the model. Similarly, a model with a number of interaction terms may also prove more accurate in making individual predictions. This might occur if, for instance, the impact of certain covariates differed systematically by others. Thus, from the perspective of being a better predictor, models may incorporate interactions that make them more difficult to interpret readily. In this study, we present separate analyses for younger and older age groups and by gender to indicate how profiling with the same instrument performs across groups within the same client group.

2.3 The procedure adopted in profiling clients and diagnosing predictive accuracy

This section explains how one moves from the construction of models predicting employment and benefit outcomes to the evaluation of the effectiveness of those models in correctly predicting outcomes:

1 Develop a set of alternative statistical models for the probability of being out of work/in receipt of out-of-work benefits/percentage of time on out-of-work benefits.

2 Run these models on a random sub-set of the sample (the ‘estimation sample’).

3 Generate predicted values for the validation sample using the estimated model.

4 Choose models which statistical tests indicate give the most accurate predictions for the validation sample who were randomly excluded from the estimation sample.

5 Adopt a ‘decision rule’ – that is, a level of probability which is used as the cut-off point for taking action in determining treatment.

6 Evaluate the predictive power of the profiling model by computing the number of correct and incorrect predictions that it yields.

Step **1** has already been discussed in Chapter 4. Usually one uses within-sample statistics to establish how well a model fits the data. However, profiling entails forecasting individuals’ benefit outcomes so within-sample measures of goodness-of-fit are not appropriate. What matters is the model’s ability to rank clients accurately according to future benefit outcomes. Steps **2**-**4** describe the technique we adopt to do this, sometimes referred to as cross-validation. It entails testing the validity of the estimation model beyond the estimation sample by making out-of-sample predictions. Predictions are made for each client based on estimates for a random sub-set of the client group. The estimation sample – which in our case comprises 70 per cent of the whole sample – is used to estimate the coefficients for the prediction model. This model is then validated using the 30 per cent validation sample, the choice between models being made by selecting the model that fits the validation sample best. There are various ways in which one might use individuals' predicted outcomes to compare models' predictive power. We follow Black, Smith, Plesca and Shannon (2002) by doing the following:

- Take the validation sample and rank individuals into quintiles (i) randomly (ii) according to their rank in the distribution of predicted outcomes. Having done this, we compare differences in the means of *actual* outcomes (whether out of work 12 months after their claim for benefit, whether claiming out-of-work benefits 12 months after their claim for benefit, or percentage of time spent claiming out-of-work benefits through to end December 2002) by quintiles of the randomly assigned and predicted outcome distributions. This comparison establishes how well profiling might target resources relative to random allocation. Clearly, profiling is of no value if it does no better than random allocation in identifying those with the highest probabilities of long-term benefit receipt.

- Compare differences in mean *predicted* outcomes throughout the distribution of predicted outcomes, measuring differences in mean predicted outcomes in the following parts of the predicted distribution:

  – top 80 per cent versus bottom 20 per cent;

  – top 60 per cent versus bottom 40 per cent;

  – top 40 per cent versus bottom 60 per cent;

  – top 20 per cent versus bottom 80 per cent.

If a model has good predictive power then the percentage of clients out of work/on out-of-work benefits/percentage of time on out-of-work benefits will be large for the top predicted quintiles and small for the bottom predicted quintiles. Ideally, a model will perform well at all points of the distribution of the predicted outcome, in which case, all four comparisons above should show sizeable differences. We also report an average of the four differences in predicted outcomes which is a summary measure of the model's predictive performance throughout the distribution.

In practice, DWP may want to use profiling to screen individuals in or out of treatment. Step **5** above is needed to convert probabilities into decisions about whether to take action or not. Thus a 'decision rule' is adopted. This entails fixing a threshold or cut-off point – for instance, a predicted probability of 50 per cent or more. Having chosen the decision rule, step **6** involves the prediction method being evaluated by comparing predicted outcomes with observed outcomes in the validation sample, and calculating the proportion of correct and incorrect predictions. Payne *et al.* (1996) show that the cut-off level in step **5** is very important in determining the relative proportion of false positives and false negatives. If the cut-off point is set high, so that only those with a high probability of remaining on benefit for a long time are treated, the proportion of false positives is reduced (reducing resource wastage) but at the cost of failing to pick up many who would benefit from early help. Conversely, if the cut-off point is set low, models succeed in identifying more of those who become long-term unemployed but at the cost of an increase in wasted resources. The relationship between the chosen cut-off point and the actual distribution on the outcome variable go some way to determining the accuracy of the profiling model. We illustrate these points in detail later using three different cut-off points (30 per cent, 50 per cent, and 70 per cent). To illustrate the point in broad terms, in an extreme case where only five per cent of claimants move into employment, a model which says 'nobody ever gets a job' will be accurate in 95 per cent of cases, which seems 'good' but the model is, nevertheless, unable to identify those who do not need help. Imagine another scenario where 80 per cent would have obtained a job without help, but the cut-off is set at 50 per cent so that half the eligible group are to be treated in any event. In this case, the maximum percentage who could have been helped into work without treatment is 20 per cent so that, even if this 20 per cent are all correctly included in the treated group, deadweight will still be 60 per cent. The cut-off approach to assessing accuracy is helpful in comparing the practical impact of allocating resources under different profiling models, but it can tell us nothing about the performance of profiling relative to Personal Adviser discretion or deterministic rules in allocating resources.[13]

[13] For Switzerland, Lechner and Smith (2003) find caseworkers do not do a very good job of allocating resources across claimants to maximise their subsequent employment prospects.

3 Analysis and results for the sick and disabled

- 70 per cent of the sick and disabled were out of work 12 months after making a claim, and 66 per cent were claiming out-of-work benefits. In the 30 months since claiming, 46 per cent had spent all their time claiming and the mean time spent claiming was 70 per cent.
- Profiling outperforms random allocation of the treatment because the models are good at ranking individuals according to profiled outcomes.
- 'Full' models tend to outperform other models, indicating that there is value to the collection of additional data. However, profiling does not necessarily improve with the addition of further variables as indicated, for instance, by the similarity between the diagnostic tests for the parsimonious and 'middling' models.
- The functional form of the model does not make a great deal of difference to profiling accuracy. In the case of out-of-work and benefit status 12 months after claiming, the logit is marginally preferable to the OLS and probit while, in the case of percentage of time spent claiming, the OLS estimator marginally outperforms the tobit.
- The success in targeting the treatment through profiling depends on the proportion of the eligible group to be treated relative to the proportion who actually go on to be out of work/claim.
- The inclusion of ward-level deprivation data did not improve the accuracy of profiling.
- The exclusion of benefit area dummies makes little difference to the predictive accuracy of the models.
- Models perform differently across sub-groups of clients but all work reasonably well in terms of the profiling diagnostics.
- Confining the analysis to claimants only does not make much difference.
- Altering the size of the estimation versus validation samples does not make much difference.
- The predictive power of profiling models for out-of-work benefit status and out-of-work labour market status is similar.

- Determinants of benefit and out-of-work status 12 months after claiming are similar, but differ in some respects, perhaps suggesting the need to develop alternative models for both outcomes. The determinants of percentage of time claiming over 30 months differ in a number of ways from benefit status at month 12.
- There are no unambiguous advantages to using percentage of time spent claiming rather than benefit status at month 12 as the profiling variable: the relative performance of profiling on these two outcomes using identical models differs with the cut-off point chosen to allocate treatment. With a 70 per cent cut-off the correct prediction rate is higher when using percentage of time spent claiming, but profiling based on wave two benefit status results in slightly better profiling with 30 per cent and 50 per cent cut-offs.

This section reports analysis and results for the sick and disabled clients in the ONE database. In the ONE data, a respondent is classified as sick or disabled if they initially asked about a sickness or disability benefit, whether or not they went on to claim the benefit. 4,785 were interviewed at the first interview and 3,048 were interviewed at the second interview.

3.1 Outcomes for the sick and disabled

Table 3.1 shows the labour market status of sick and disabled respondents 12 months after their claim for benefit: only 30 per cent were doing any paid work at that point, the remaining 70 per cent were distributed across the categories emboldened in the table.

Table 3.1 Labour Market Status 12 months after their claim for benefit

	Weighted column percentage
30+ hours paid work	20.7
16-29 hours paid work	6.0
<16 hours paid work	3.1
Full-time education	**1.3**
Government scheme	**0.8**
Unemployed	**9.6**
Looking after home	**6.0**
Temporarily sick or injured	**21.0**
Permanently sick or disabled	**28.8**
Not working, other reasons	**2.8**

Note: unweighted N=3,048

Table 3.2 Out-of-work benefits received 12 months after their claim for benefit

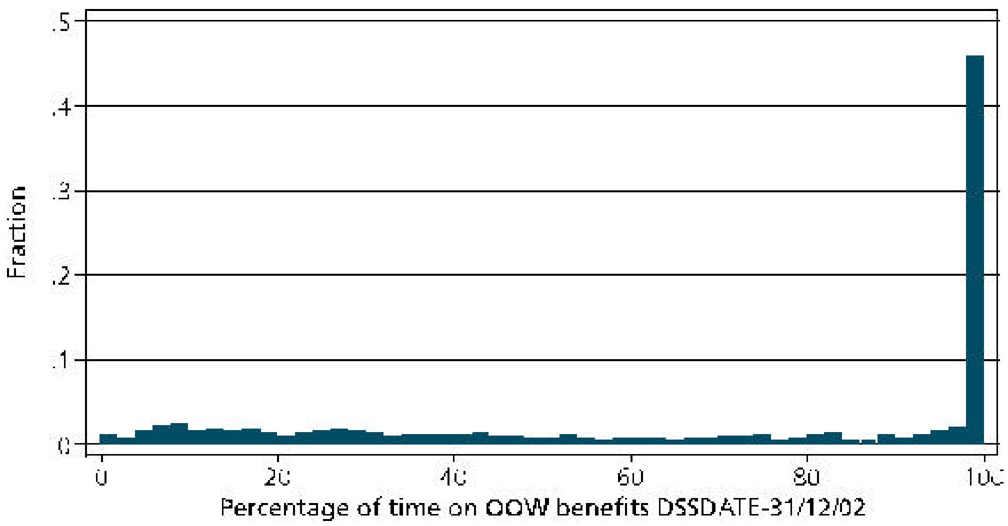
	Weighted cell percentage
Income Support	31.8
Jobseeker's Allowance	8.8
Widow's Benefit	0.8
Incapacity Benefit	36.1
Invalid Care Allowance	2.1
Severe Disablement Allowance	26.9
Any of the above	66.4

Note: unweighted N=3,040. There were eight cases whose benefit status could not be accurately determined

Table 3.2 identifies what out-of-work benefits sick and disabled respondents said they were receiving 12 months after their claim for benefit. Sixty-six per cent of respondents received at least one of the six out-of-work benefits identified. Fifty-three per cent of respondents were in receipt of a single out-of-work benefit, with 13 per cent receiving two or more.

We were able to match 96.8 per cent (4,631 out of 4,785) of the sick and disabled clients who responded at wave one to administrative benefit records.[14] Almost half (46 per cent) of wave one respondents had spent all of their time on one or more of the out-of-work benefits qualifying clients for ONE (JSA, IS, IB, ICA, SDA, WB or BB), with the remainder spread fairly evenly across the rest of the distribution (Figure 3.1).

Figure 3.1 Percentage of time spent on out-of-work benefits between ONE eligibility and 31 December 2002



3.2 Models used in profiling the sick and disabled

Figure 3.2 shows the variables used in the parsimonious (column 1), middling (column 2) and full models (column 3) for the sick and disabled. In each case, there are two versions of the model, with Models (1), (3) and (5) using the six dummy variables to distinguish the three types of pilot area and their respective control areas, and Models (2), (4) and (6) replacing these with 24 benefit area dummies.

3.3 The analyses undertaken and sensitivity testing

Analyses for the three outcomes described in Section 3.1 are presented in turn below. The sensitivity of profiling results to model specification is explored with the six 'baseline' models containing the independent variables listed in Figure 3.2. This allows us to compare results for a parsimonious model with those for a 'middling' and 'full' model, as well as allowing us to account for any ONE evaluation effects in two ways, that is, through a set of six pilot/comparison area controls and the 24 area dummies.

[14] The 154 cases with no match may have never claimed out-of-work benefits, or else there is a problem with their National Insurance Number. They are excluded from the analysis of this dependent variable.

Figure 3.2 Variables used in models profiling the sick and disabled

Models (1)-(2)	Models (3)-(4) – as (1) and (2) plus:	Models (5) and (6) – as (3) and (4) plus:
Demographics Gender 8 age dummies White7 education dummies If numeracy problems If literacy problems 6 housing tenure dummies **Benefit history in 2 yrs pre-ONE** If ever received out-of-work benefits only If received in-work benefits only If received both out-of-work and in-work benefits If received no benefits **Work history in 2 yrs pre-ONE** 6 dummies for % time working 16+ hours per week 3 dummies for % time working 1-15 hours per week If ever unemployed **Area** TTWA benefit stocks/flows for unemployment, lone parents, sick and disabled 6 dummies for ONE/comparison areas, OR 24 benefit area dummies	**Demographics** 6 marital status dummies 4 dummies for number of children **Work history in 2 yrs pre – ONE** 6 net pay in pre-ONE job dummies 6 social class in last pre-ONE job dummies Date of ONE entry 5 dummies identifying any time in the following states: – temporarily sick – permanently sick/ disabled – full-time education – training – other (eg. looking after home)	**Demographics** 3 dummies for general health in last year 3 dummies for long-standing illness Mental disability dummy 3 care responsibility dummies If possess telephone 3 dummies for vehicle access and licence 3 dummies for number of household workers 5 dummies for work attitudes

We test the sensitivity of the profiling results to variations in the functional form of the model. In the case of outcomes 12 months after their claim for benefit, we compare OLS, probit and logit estimators and, in the case of the percentage of time spent claiming between ONE eligibility and end December 2002, we compare OLS and tobit specifications. Our models are run on estimation samples that are a 70 per cent random sample, with the remaining 30 per cent making up the validation sample. We choose this split, rather than the 90:10 split common in the U.S. UI literature, because our sample sizes are not as large as those common in the U.S. and we are concerned to ensure robust validation, even at the expense of some greater imprecision in our estimation. We test the sensitivity of our results to an 80:20 split.

Analyses are based on the whole sample, regardless of whether they said they went on to claim an out-of-work benefit on becoming eligible for ONE. However, we test the sensitivity of results to the exclusion of the relatively small number of clients who did not go on to claim.

We test the sensitivity of results to inclusion of ward-level data on deprivation. Finally, we test the performance of the profiling model on four sub-groups within the sick and disabled sample, namely men, women, those aged under 45 years, and those aged 45 or more. These results are based on separate profiling models for these client groups using identical sets of covariates.

3.4 Results

We present results for each of our three dependent variables in turn, adopting a similar format in each case.

3.4.1 Without a job twelve months after their claim for benefit

Table 3.3 Comparison of proportions out of work 12 months after their claim for benefit, by quintiles of predicted out-of-work status for logit, probit and OLS

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Q5	.94	.97	.94	.96	.95	.95
Q4	.77	.83	.77	.82	.76	.83
Q3	.72	.70	.72	.71	.71	.68
Q2	.58	.63	.56	.62	.59	.67
Q1	.42	.29	.45	.30	.42	.28

Note: all models run on 70 per cent sample and results based on 30 per cent validation sample

Table 3.3 shows the mean proportion of the sick and disabled who were without paid work at the wave two survey interview in each quintile of the predicted distribution of out-of-work probabilities. It does so for the logit, probit and OLS specifications of Models (2) and (6), namely the most parsimonious and fullest models containing the 24 area dummies. Recall that, in the raw data, 70 per cent of the sample was out of work at that stage, roughly one year after ONE eligibility. If ranked according to actual outcomes, the proportions in Q5-Q3 would be 1, the proportion in Q2 would be .5 and the proportion in Q1 would be zero. Ranking claimants according to their predicted probability of being out of work twelve months after their claim for benefit, depending on the model, 94-97 per cent of the highest quintile actually go on to be out of work, compared with 29 – 45 per cent of those in the lowest quintile of predicted probabilities. Three points emerge from the table:

- First, all models do a reasonable job at ranking individuals according to their future out of work status, as indicated by the sizeable differences in mean actual outcomes across the predicted outcome distribution.
- Second, the full models do a better job than the parsimonious models at identifying those with the lowest out-of-work probabilities, as indicated by the lower proportions out of work in the lowest predicted quintiles derived from full models relative to parsimonious models.
- Third, there is little to choose between the performance of the different functional forms.

It is clear from Table 3.3 that allocation through profiling is preferable to random allocation of treatment. If one ranks clients randomly, the mean proportion out of work in each quintile fluctuates around .7, whereas, using the predictions from any of the estimation methods, profiling does a much better job at identifying which clients are likely to remain out of work a year later.[15]

Table 3.4 compares the predictive performance of the logit, probit and OLS using Models (2), (4) and (6). It presents differences in the proportion predicted out of work between the top and the bottom of the distribution of predicted probabilities. For example, the .41 in column 1 row 1 means that, using predicted probabilities generated by Model (2) with a logit functional form, the mean predicted probability of being out of work was 41 percentage points higher for the top 80 per cent of the predicted probability distribution in the validation sample than the mean for the bottom 20 per cent. The average difference at the bottom of column 1 is simply the average of the four differences above it.

Table 3.4 Differences in proportion predicted out-of-work, by quintiles of the predicted probability distribution

	Logit			Probit			OLS		
	M(2)	**M(4)**	**M(6)**	**M(2)**	**M(4)**	**M(6)**	**M(2)**	**M(4)**	**M(6)**
T80%-B20%	.41	.43	.54	.40	.42	.53	.35	.36	.44
T60%-B40%	.39	.39	.48	.38	.39	.47	.34	.35	.41
T40%-B60%	.37	.37	.42	.37	.37	.42	.36	.36	.42
T20%-B80%	.34	.34	.36	.34	.35	.37	.39	.39	.45
Average dif.	.38	.38	.45	.37	.38	.45	.36	.36	.43

Note: models with 24 area dummies; T=top, B=bottom; estimation sample = 2134; validation sample = 914

Comparing the average differences in predicted outcomes across functional forms, the logit outperforms the probit and OLS models, though the differences are not great. The predictive power of the models is not driven by 'success' in any particular part of the distribution, though there is evidence that the OLS is better at predicting throughout the distribution. For the logit and probit models, mean differences decline as one moves from row 1 to row 4, something that does not happen in the case of the OLS. Comparing the average differences in predicted outcomes across Models (2), (4) and (6), even the most parsimonious model performs reasonably well. There is no gain moving from (2) to (4), but there are clear gains in profiling with Model (6), as indicated by an average difference of seven percentage points over the other models.

Table A.2 presents Models (1) – (6) using the logit estimator to illustrate which variables in the models are statistically significant (Table A.1 gives the meaning of variable labels used in the sick and disabled models). In the most parsimonious models (1) and (2), probabilities of being out of work 12 months after their claim for benefit rise with age, being a woman, a lack of qualifications, numeracy problems and living in rented accommodation (whether privately or from the local authority). They also rise in two of the three area control-types (basic and PVS). Work history in the two years before ONE eligibility is important, with out-of-work probabilities falling with time spent in full-time paid work, substantial part-time work, any time unemployed, and receipt of in-work benefits over that period. These results generally apply to Models (3) and (4) too. However, additional work history variables, such as social class and earnings in the last pre-ONE job, and other labour market statuses in the two years prior to ONE, were not significant. Nor was the date of eligibility for ONE. Marital status and

[15] We confirmed this in analysis by simulating randomly allocation of individuals to treatment.

number of dependent children are included for the first time in Models (3) and (4). Widows had a lower probability of being out of work than single people, and those with two children had a lower probability of being out of work than those with one child, but these variables add little to the model. These two sets of variables have stronger effects in the fullest models, (5) and (6), where single people have a higher probability of being out of work than widows and divorcees, while those with one child have higher probabilities of being out of work than those with no child and those with two children. As discussed in Section 2.2.3, these 'full' models contain variables that may well have been affected by benefit claiming, so their effects must be interpreted with caution. Most prove significant. Probabilities of being out of work rise with perceived poor health (general health, long-standing illness, mental illness) and care responsibilities. Probabilities of working are enhanced where the sick and disabled have a driving licence and access to a vehicle, where others in the household are working, and where their attitudes towards working are very positive.

In Table 3.5, we turn our attention to the issue of how good these profiling models are at targeting treatment on the right clients, by which we mean those who go on to be longer-term claimants. Taking the logit Models (2) and (6) discussed above, the table identifies the percentages in the validation sample who are correctly predicted (column 1), those who are correctly treated (column 2), those who are wrongly treated (column 3), and those who are wrongly denied access to treatment (column 4) at three different cut-off points for treatment. Columns 1, 3 and 4 add to 100 since each person must be in one of these three mutually exclusive categories.[16] The 30 per cent cut-off simulates a treatment offered to the majority (70 per cent) of eligible clients while, at the other extreme, the 70 per cent cut-off simulates a tightly targeted treatment only received by 30 per cent of the eligible population.

Three points emerge clearly from the table:

- First, with a large target group, nearly three-quarters of the sample are correctly predicted. The correct prediction rate falls as the treatment becomes more targeted, but remains at 58 per cent for the treatment targeted at 30 per cent of the eligible group. It is not surprising that the models are best able to predict accurately where 70 per cent are to be treated, since around 70 per cent actually go on to be out of work 12 months after their claim for benefit. As Waddell, Burton and Main (2003: 10) note: 'the practical consequences of applying a screening tool (as summarized by the predictive values) depend crucially on the prevalence of the outcome in the particular population'.

- Second, model specification makes some difference, though the differences are not large. With a 30 per cent or 50 per cent cut-off point the full model makes correct predictions in 3 – 4 per cent more cases than the most parsimonious model. There is no difference with a 70 per cent cut-off.

- Third, as the target group for treatment rises, so the percentage of the eligible group who are wrongly treated rises, while the percentage who are wrongly denied falls. Of course, if everyone was treated, no-one would be wrongly denied. In our case, 14 – 15 per cent of the validation sample are wrongly treated at the 30 per cent cut-off point. That is, 14 – 15 per cent were in the top 70 per cent of out-of-work predictions but went on to get a job by wave two. This figure falls to under one-in-ten with a 50 per cent cut-off and a mere 2-3 per cent with a 70 per cent cut-off. Conversely, with a 30 per cent cut-off, 12 – 14 per cent of cases are wrongly denied treatment, but this rises to 39 – 41 per cent when the cut-off is lifted to 70 per cent.

[16] Where they do not add to 100 this is due to rounding.

Table 3.5 Success in targeting treatment at different cut-offs for treatment allocation using out-of-work probabilities twelve months after their claim for benefit

	Correctly predicted	Correctly treated	Wrongly denied	Wrongly treated
30% cut				
M(2)	71	55	15	14
M(6)	74	57	14	12
50% cut				
M(2)	65	43	9	26
M(6)	69	45	7	24
70% cut				
M(2)	58	29	3	41
M(6)	58	30	2	39

Note: treatment allocation in validation sample. 30 per cent cut = OOW prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = OOW prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = OOW prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on logit model.

The figures in Table 3.5 are percentages of the whole validation sample. In Table 3.6 we express the same information in a different fashion to shed further light on the success of the models in targeting treatment. The first row simply reports the percentage of wrong predictions at different cut-off points. The wrong prediction rates are not trivial, and rise with more targeted treatment. The second row shows the wrong prediction rate is particularly high among those predicted not to need treatment. With a 50 per cent cut-off, half those predicted not to need treatment are actually out of work 12 months after their claim for benefit. This rises to 57 per cent with a 70 per cent cut-off. On the other hand, row three shows a relatively small percentage of those who are predicted to need treatment actually find a job – 20 per cent in the case of the 30 per cent cut-off, falling to six per cent with a 70 per cent cut-off. The last two rows use actual out-of-work status 12 months after their claim for benefit as their base. Row 4 shows close to half (45 per cent) of those in work 12 months after their claim for benefit would have been wrongly treated as a result of their profiling prediction where 70 per cent of the sample is treated. This falls to six per cent where only 30 per cent of the sample are treated. Finally, row 5 shows over four-fifths of those who actually went on to be out of work 12 months after their claim for benefit would have been treated following profiling with a treatment aimed at 70 per cent of the sample. This falls to 43 per cent in a smaller programme where only 30 per cent are treated.

Table 3.6 Prediction rates at different cut-offs for treatment allocation using out-of-work probabilities twelve months after their claim for benefit

	30% cut	50% cut	70% cut
Percentage all predictions wrong	26	31	42
Percentage all negative predictions wrong	41	50	57
Percentage all positive predictions wrong	20	13	6
Percentage in work wrongly treated	45	23	6
Percentage out of work correctly treated	83	65	43

Notes: prediction rates in validation sample based on M(6) results presented in Table 3.5

It is difficult to judge whether the prediction rates reported in Tables 3.5 and 3.6 are sufficiently accurate to merit profiling as a resource allocation tool because we need to be able to compare success rates under profiling with those achieved through Personal Adviser discretion or the application of deterministic rules relating to current length of claim spell. Success rates for these alternative resource allocation mechanisms are not available. Of course, we can compare them to a system based on the simplest deterministic rules, namely the treatment of all and the treatment of none. Where all are treated, irrespective of future job prospects, 70 per cent will be correctly treated, 30 per cent wrongly treated and 0 per cent wrongly denied. Conversely, where none are treated, 0 per cent are correctly treated, 0 per cent are wrongly treated, and 70 per cent are wrongly denied.

Having presented our basic results for this outcome we turn to our sensitivity tests. Throughout, Models (1) and (5) are used to present results for these sub-sample analyses because these avoid use of the 24-category benefit area variable which, when sample sizes fall, results in the rejection of some cases due to perfect prediction of the outcome in benefit areas with small cell sizes.

First, we consider whether the results alter with the inclusion of variables picking up ward-level deprivation. Analyses were rerun for the English sub-sample with valid ward identifiers.[17] Because the deprivation indices are highly correlated, they were entered separately into models. We tested the impact of the multiple deprivation, employment deprivation and health deprivation indices first as linear terms, and then by breaking the indices into quartiles. Although some of these deprivation indices were statistically significant in some models, their inclusion had no effect on the profiling diagnostics. This is not to say that ward deprivation is unimportant: the deprivation measures relate to data for the period 1998 – 99, whereas we are trying to predict outcomes for clients approaching DWP about benefit claims in 2000. Recent research indicates substantial change in deprivation at ward level between 1998 – 2000, implying some measurement error in applying the 2000 indices to the ONE data. New ward-level measures of deprivation will be available shortly and may be worth investigating for their profiling potential.[18] It may also be worth investigating small area Census data on measures such as car ownership rates.

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[17] Of the 4,785 sick and disabled in the ONE data, 153 had no identifiable claimant administrative records. A further 597 were linked to administrative data but had no ward identifier that could be matched to the deprivation data. In 586 cases this was because the client lived in Scotland or Wales. Thus, 4,035 of the 4,785 sick and disabled had ward identifiers linking to the deprivation data. The use of ward-level deprivation data reduced the sample for analysis of wave two out-of-work status from 3,048 to 2,539 cases.

[18] We thank Mike Noble, University of Oxford, for this information.

Table 3.7 Comparison of whole sample versus claimant only models

	Whole sample		Claimants only	
	M(1)	M(5)	M(1)	M(5)
T80%-B20%	.38	.52	.40	.53
T60%-B40%	.37	.46	.38	.47
T40%-B60%	.36	.41	.37	.42
T20%-B80%	.33	.36	.34	.37
Average difference	.36	.44	.37	.45
30% cut				
Correctly predicted	71	75	75	77
Correctly treated	56	58	58	59
Wrongly treated	15	14	13	12
Wrongly denied	14	12	12	11
70% cut				
Correctly predicted	57	59	57	58
Correctly treated	29	30	29	30
Wrongly treated	3	2	2	2
Wrongly denied	40	39	40	40

Note: logits for sick and disabled OOW status at wave 2. T=top, B=bottom. For whole sample, estimation sample = 2134, validation sample = 914. For claimant only sample, estimation sample = 1924 and validation sample = 825

Second, we re-estimated our models excluding the benefit area variables to see what impact their exclusion had on the predictive power of the profiling. Their exclusion makes very little difference to the accuracy of profiling. The average differences for logit Models (2), (4) and (6) were .36, .35 and .44 respectively, compared with .38, .38 and .45 in the models presented in the first three columns of Table 5 that contained benefit area dummies. Correct prediction rates are virtually identical: 71 per cent and 75 per cent for Model (2) and (6) with a 30 per cent cut-off and 58 per cent and 59 per cent for the same models with a 70 per cent cut-off. These compare with figures of 71 per cent, 74 per cent, 58 per cent and 58 per cent for the identical models including benefit area dummies (see Table 6).

Our third sensitivity analysis entailed varying the 70:30 estimation versus validation sample split used above, this time running models on a random 80 per cent of the sample (N=2,438 instead of 2,134), thus reducing the validation sample to 610. Inspection of the models run on the 80 per cent random sample showed the signs on all variables were the same as models run on the 70 per cent random sample, but coefficients and the pattern of significant results differed in some cases. Identical diagnostic tests were performed to those reported for the 70:30 split. Differences in out-of-work predictions across quintiles of the predicted probabilities were very similar, as were the percentage of correct predictions. We therefore prefer the 70:30 split to ensure a robust validation sample.

Our fourth sensitivity test involved confining the sample to those respondents who said at the wave one interview that they had made a claim for benefits. This meant dropping 210 cases from the analysis. Table 3.7 compares the profiling diagnostics for this claimant-only sample with the whole sample analysis, using logit models (1) and (5). The models are similar in terms of the differences in mean predicted probabilities across quintiles, with the claimant-only models performing slightly better. The claimant-only model also performs a little better than the whole sample model in terms of correct predictions, though only when using the 30 per cent cut-off.

Finally, we present some sub-group analyses by gender and by age. These results are based on separate profiling models for each sub-group, using identical covariates. There are differences in the impact of variables between men and women. For example, numeracy problems only raised the probability of being out of work for men, whereas the positive effect of literacy problems was confined to women. The most notable difference in the models, however, was the non-significance of many effects for women. Table 5.8 presents diagnostics for separate models run for men and women. Using the average difference criterion, the models for women do not perform as well as those for men, but they still perform well. Correct prediction rates are also fairly similar, particularly when using the 70 per cent cut-off. It seems there is little to distinguish the performance of the profiling models across men and women, despite the significance of more variables in the models for men.

Table 3.8 Diagnostics for out-of-work status twelve months after their claim for benefit, men and women

	Men		Women	
	M(1)	M(5)	M(1)	M(5)
Average difference	.40	.49	.38	.44
Percentage correct predictions (30 per cent cut-off)	70	77	72	74
Percentage correct predictions (70 per cent cut-off)	57	56	57	57

Note: Logits, with 70 per cent estimation sample, 30 per cent validation sample

Testing age effects, we split the sample into those aged 45 and over and those aged under 45 and ran separate profiling models for both groups. Inspection of coefficients showed the main difference in the models was the non-significance of some effects for under-45s. Diagnostics are presented in Table 3.9. Average differences in predicted outcomes were, nevertheless, higher for the under-45s in Model (1), but there was no difference for Model (5). With a 30 per cent cut-off, correct prediction rates were better for under-45s than they were for those aged 45+ with Model (1), but were better for the older age group than the younger age group in Model (5). Correct prediction rates were nearly identical by age with the 70 per cent cut-off. Taken together, these results suggest the models used worked equally well for under-45s and those aged 45 and over.

Table 3.9 Diagnostics for out-of-work status 12 months after their claim for benefit, by age

	Less than 45 years		45+ years	
	M(1)	M(5)	M(1)	M(5)
Average difference	.40	.46	.35	.46
Percentage correct predictions (30 per cent cut-off)	73	75	71	78
Percentage correct predictions (70 per cent cut-off)	54	56	54	57

Logits, with 70 per cent estimation sample, 30 per cent validation sample

We can draw the following inferences from the analysis presented above:

- Profiling outperforms random allocation of the treatment because the models are good at ranking individuals according to their probabilities of being out of work.
- The 'full' model outperforms the other models, indicating that there is value to the collection of these additional data. However, profiling does not necessarily improve with the addition of further variables, as indicated by the similarity between the diagnostic tests for the parsimonious and middling models.
- Functional form of the model does not make a great deal of difference, although the logit is marginally preferable to the OLS and probit.
- The success in targeting the treatment through profiling depends on the proportion of the eligible group to be treated relative to the proportion who actually go on to be out of work.
- The inclusion of ward-level deprivation data did not improve the accuracy of profiling.

- The exclusion of benefit area dummies makes little difference to the predictive accuracy of the models.
- Models perform differently across sub-groups of clients but all work reasonably well in terms of the profiling diagnostics.
- Confining the analysis to claimants only does not make much difference.
- Altering the size of the estimation versus validation samples does not make much difference.

3.4.2 Claiming out-of-work benefit 12 months after their claim for benefit

Identical analyses were undertaken to predict the probability of claiming at least one of six out-of-work benefits (IS, JSA, IB, ICA, SDA, WB) at the second wave interview. As shown in Table 3.2, around two-thirds of wave two respondents said they were in receipt of these out-of-work benefits. In fact, 6.5 per cent of those saying they were in receipt of out-of-work benefits also said they were doing some paid work, including 4.7 per cent who said they were doing paid work of 16 hours or more per week. We test the sensitivity of results to the exclusion of this group since, in most instances, working these hours would debar them from these out-of-work benefits.

Table 3.10 compares proportions of sick and disabled clients in receipt of out-of-work benefits 12 months after their claim for benefit when a) ranked according to their predicted probability of benefit receipt (columns 1 and 2) b) randomly allocated to quintiles. Recall that, in the raw data, 66 per cent of the sample were in receipt of out-of-work benefits at that point. If ranked according to actual outcomes, the proportions in Q5-Q3 would be 1, the proportion in Q2 would be 0.3, and the proportion in Q1 would be zero. If one ranks clients randomly the mean proportion on out-of-work benefit in each quintile fluctuates around .66 (column 3), as expected, whereas using the predictions from Models (2) and (6) of the logit specification to illustrate, profiling does a much better job at identifying which clients are likely to be benefit claimants a year after ONE entry. Model (6) does a better job at this than Model (2), especially for the lowest quartile of the predicted outcome distribution. Mean benefit receipt rates by predicted quintile in Table 3.10 are very similar to mean out-of-work rates for the equivalent logit models in the first two columns of Table 3.3.[19]

Table 3.10 Comparison of profiling and random allocation on actual receipt of out-of-work benefits twelve months after their claim for benefit

	Quintiles of predicted probability distribution from M(2)	Quintiles of predicted distribution distribution from M(2)	Randomly assigned quintiles
Q5	.92	.92	.64
Q4	.79	.84	.66
Q3	.67	.70	.71
Q2	.48	.57	.67
Q1	.44	.26	.66

Note: logit models run on 70 per cent sample, results based on 30 per cent validation sample. Outcome is any out-of-work benefit received at wave 2.

[19] Remember raw means for the out-of-work rate and receipt of out-of-work benefits are similar (70 per cent and 66 per cent respectively).

Table 3.11 compares the predictive performance of the logit, probit and OLS using Models (2), (4) and (6). Comparing across functional forms, the average differences in predicted outcomes are small. In each case, the most parsimonious model, M(2), performs reasonably well, but there are clear gains in moving from M(2) to M(4), and further gains moving to the fullest model, M(6).

Table A.3 presents Models (1) – (6) using the logit estimator to illustrate which variables in the models have a significant impact predicting out-of-work benefit status 12 months after their claim for benefit. In many ways, their effects are similar to those presented in Table A.2 for out-of-work labour market status. However, there are some notable differences. For example, being female is no longer significant; age effects disappear in the fullest models; education effects are quite different, notably the significant negative effect of having a foreign qualification in the benefit model; in contrast to the out-of-work labour market models, having claimed in-work benefits in the two years prior to ONE eligibility is not significant, whereas claiming out-of-work benefits in that period increases the probability of doing so again after ONE entry; there are strong negative effects of cohabitation and time spent in education pre-ONE; care effects are stronger; and work attitude effects are weaker. It seems the determinants of benefit status differ somewhat from the determinants of labour market status.

Table 3.11 Differences in the proportion predicted to be receiving out-of-work benefits, by quintiles of the predicted probability distribution

	Logit			Probit			OLS		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	.34	.39	.51	.33	.38	.50	.30	.34	.45
T60%-B40%	.32	.37	.45	.32	.36	.44	.30	.33	.41
T40%-B60%	.32	.35	.40	.32	.35	.41	.31	.34	.41
T20%-B80%	.33	.33	.36	.32	.34	.37	.35	.38	.45
Average dif.	.32	.36	.43	.32	.36	.43	.32	.34	.43

Note: models with 6 ONE dummies; T=top, B=bottom; estimation sample = 2128; validation sample = 912

A comparison of average differences in predicted outcomes from benefit receipt models in Table 3.11 and labour market status models in Table 3.4 indicates that the benefit receipt models are not so good at ranking clients as the labour market status models. However, the exclusion of the five per cent or so of sick and disabled clients working 16 hours or more per week, yet said they were in receipt of out-of-work benefits, improved the predictive power of the model. For example, the average difference in predicted benefit status 12 months after their claim for benefit was .47 with M(6) having excluded the workers. Estimation for this sub-group also altered the size, and sometimes the statistical significance, of coefficients in the model. For instance, the exclusion of these 'odd' cases resulted in stronger effects for age and out-of-work benefit receipt pre-ONE.

Table 3.12 shows how good the profiling models are at targeting treatment on those who go on to claim out-of-work benefits 12 months after their claim for benefit. The results are based on logit Models (2) and (6) and are thus comparable to those presented for out-of-work labour market status in Table 3.5. The correct prediction rate (column 1) for benefit receipt is at least as good, and sometimes better, than that for labour market status. This is the case, even though – as reported above – the average differences in predicted outcomes are not so good. The proportions wrongly denied treatment are a little lower than in the case of the out-of-work labour market predictions, whereas the proportions wrongly treated are similar or higher. However, these differences are very small – always one or two percentage points – so, in essence, the models perform equally well in predicting labour market and benefit status 12 months after their claim for benefit.

Table 3.13 shows, again, how closely the predictive power of the benefit receipt models resemble that for the out-of-work labour market status. A comparison with Table 3.6 shows the only big difference between the models is the lower percentage of all negative predictions that are incorrect in the benefit receipt model.

Table 3.12 Success in targeting treatment at different cut-offs for treatment allocation using out-of-work benefit receipt probabilities twelve months after their claim for benefit

	Correctly predicted	Correctly treated	Wrongly predicted	Wrongly treated
30% cut				
M(2)	71	54	17	12
M(6)	76	57	14	10
50% cut				
M(2)	67	42	9	24
M(6)	70	44	8	23
70% cut				
M(2)	58	28	4	39
M(6)	59	29	3	38

Note: treatment allocation in validation sample. 30 per cent cut = OOW benefit prediction at 30^{th} percentile (so 70 per cent treated); 50 per cent cut = OOW benefit prediction at 50^{th} percentile (so 50 per cent treated); 70 per cent cut = OOW benefit prediction at 70^{th} percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on logit model.

Table 3.13 Prediction rates at different cut-offs for treatment allocation using out-of-work benefit receipt probabilities twelve months after their claim for benefit

	30% cut	50% cut	70% cut
Percentage all predictions wrong	24	30	41
Percentage all negative predictions wrong	34	48	56
Percentage all positive predictions wrong	20	15	9
Percentage in work wrongly treated	42	24	9
Percentage out-of-work correctly treated	85	66	43

Notes: prediction rates in validation sample based on M(6) results presented in Table 3.11

Sensitivity tests revealed the following:

- The addition of ward-level deprivation indices has no effect on the predictive accuracy of the models.
- The exclusion of benefit area dummies has little effect on the predictive accuracy of the models.
- Average difference and correct prediction rate diagnostics indicated models run on claimants only (that is, those saying they were in receipt of one or more out-of-work benefits at wave one) performed similarly to, or better than, those run on the whole sample.
- Running the analysis on a random 80 per cent of the sample and validating it on a 20 per cent random sample had little effect on the profiling diagnostics.

- In sub-group analyses, the profiling models predicted out-of-work benefit status twelve months after their claim for benefit a little better for men than for women. For instance, the correct prediction rate using Model (5) was 76 per cent for men and 70 per cent for women. By age, the models performed a little better for under-45s than they did for those aged 45 or more.

We can infer the following from the analysis presented above:

- The predictive power of profiling models for out-of-work benefit status twelve months after their claim for benefit is similar to that for out-of-work labour market status twelve months after their claim for benefit in terms of correct prediction rates, even though average differences for the benefit models are lower.
- Determinants of benefit and out-of-work status are similar, but differ in some respects, perhaps suggesting the need to develop alternative models for both outcomes.
- Profiling out-of-work benefit status improves when one excludes those who said they were in receipt of out-of-work benefits but were also working at least 16 hours per week.
- Results were broadly similar when performing other sensitivity tests.

3.4.3 Time claiming out-of-work benefits after ONE

In this section, we turn to our third dependent variable, namely the percentage of time sick and disabled clients spent on out-of-work benefits between ONE eligibility and 31 December 2002.

Table 3.14 Percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002, by quintiles of predicted time claiming benefits OLS and tobit

	Distribution in the data	OLS			Tobit		
		M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
Q5	1.0	.89	.91	.92	.90	.92	.93
Q4	1.0	.80	.80	.82	.78	.79	.82
Q3	.89	.67	.67	.75	.68	.67	.74
Q2	.45	.64	.62	.61	.62	.61	.60
Q1	.13	.50	.50	.39	.51	.51	.40

Note: all models run on 70 per cent sample (N=3,242) and results based on 30 per cent validation sample (N=1,390)

All but ten of the sick and disabled clients became eligible for ONE in June or July of 2000, so the percentage is calculated over a period of around two and a half years. This analysis differs in two respects from the profiling for outcomes twelve months after their claim for benefit. First, as discussed in Sections 2.2.1 and 2.2.2, this dependent variable is continuous, running from 0 through to 100. However, there is bunching at the top end, with 1,911 of the 4,632 clients successfully matched to the benefit data spending all of their time since ONE eligibility on out-of-work benefits. This is reminiscent of the bunching in the US data on U.I. benefit exhaustion. Following that literature, and for reasons discussed earlier, we utilise this variance in our outcome by modelling the data with OLS and tobit functions, the latter taking account of the bunching of observations at the upper bound of the dependent variable. Second, the analysis does not rely on wave two outcome information, so the analysis is run on the larger sample who provided information at wave one for whom we found matches in the benefit administrative data. Thus, the analysis is not prone to potential bias arising from sample attrition between waves one and two. In other respects, the analysis mirrors that for the previous two dependent variables: it uses the same model specifications, and presents the same diagnostic tests.

Table 3.14 shows the percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002. The overall mean time spent on out-of-work benefits in the data is 70 per cent. If ranked according to the actual time spent claiming in the raw data, all those in the top two quintiles have been claiming out-of-work benefits throughout, while in the third quintile, the mean percentage of time spent claiming is 89 per cent (column 1). This confirms the difficulties the sick and disabled have in leaving benefits. However, with a mean of only 13 per cent in the lowest quintile, there is a sizeable proportion spending only a minority of their time on out-of-work benefits.

Ranking clients according to their predicted percentage of time on out-of-work benefits since ONE eligibility, the mean percentage of time on benefit among the highest quintile is 94-98 per cent (depending on the model), compared with 41-48 per cent among those in the lowest quintile. All models do a reasonable job at ranking individuals according to future time on benefits, as indicated by the sizeable differences in mean actual outcomes across the predicted outcome distribution. The full models do a better job than the parsimonious models in identifying those with lowest percentage of time on benefit. This is indicated by lower percentages of time on benefit in the lowest predicted quintile, derived from full models relative to parsimonious models. Comparing functional forms, there is little to choose between the performance of the tobit and the OLS. Where clients are randomly assigned to quintiles, the mean percentage of time on benefits fluctuates around 70 per cent, so profiling is clearly preferable to random allocation of treatment.

Table 3.15 Differences in percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002, by quintiles of predicted distribution

	OLS			Tobit		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	27.1	28.4	36.2	26.4	27.9	35.8
T60%-B40%	27.4	28.6	33.8	25.5	27.2	32.0
T40%-B60%	28.6	29.9	34.0	25.5	27.1	30.1
T20%-B80%	31.0	32.9	35.9	25.5	27.3	28.6
Average dif.	28.5	29.9	35.0	25.7	27.4	31.6

Note: all models run on 70 per cent sample (N=3,242) and results based on 30 per cent validation sample (N=1,390); T=top; B=bottom

Table 3.15 compares the predictive performance of the OLS and tobit using Models (2), (4) and (6). It presents differences in the average predicted time on out-of-work benefits between the top and the bottom of the distribution of predicted percentage of time claiming. For example, the 27.1 in column 1 row 1 means that, using predictions generated by Model (2) with an OLS functional form, the mean predicted percentage of time on out-of-work benefits was 27.1 percentage points higher for the top 80 per cent of the predicted distribution in the validation sample than the mean for the bottom 20 per cent. The average difference at the bottom of column 1 is simply the average of the four differences above it.

Comparing the average differences in predicted outcomes across functional forms, the OLS outperforms the tobit, and it does so for all three models. The predictive power of the models is not driven by 'success' in any particular part of the distribution. Comparing the average differences in predicted outcomes across OLS Models (2), (4) and (6), even the most parsimonious model performs reasonably well. There is some gain moving from (2) to (4), but there are clear gains in profiling with Model (6), as indicated by an average difference that is five percentage points higher than Model (4). The models appear less discriminating than those estimating whether on benefits twelve months after their claim for benefit since, with similar mean scores for both variables, the average differences presented in Table 3.11 are larger than those presented in Table 3.15.

Table A.4 presents Models (1) – (6) using the OLS estimator to illustrate which variables in the models are statistically significant. The bullet points below comment on these results, comparing them to identical OLS models (not shown) estimating the probability of being in receipt of out-of-work benefits twelve months after their claim for benefit. The commentary focuses on results that differ from those discussed in the analysis of wave two benefit receipt.

- Age: time on benefit increases with age, as does the probability of benefit receipt twelve months after their claim for benefit, but the age effects are stronger when estimating time on benefit.
- Qualifications: higher education below degree level and foreign qualifications were associated with lower probability of benefit receipt twelve months after their claim for benefit, whereas all qualifications below degree level, excluding foreign qualifications, were associated with a lower percentage of time claiming out-of-work benefits in Models (1) to (4) while, in the fullest models, degree-level qualifications lowered percentage of time claiming, with weaker effects for mid-level qualifications.
- Housing tenure: renters spend more time on benefits than home owners; the effects are stronger than they were for wave two benefit status. Also, being housed in an institution was significant throughout, whereas it was only significant in the parsimonious models for benefit receipt twelve months after their claim for benefit.
- Benefit history: the positive association between benefit receipt post-ONE and benefit history before ONE is stronger here than when estimating benefit status twelve months after their claim for benefit.
- Work history: the effects of time spent in full-time and part-time jobs are strong in estimating percentage of time on out-of-work benefits and wave two benefit status, but they are strongest for wave two benefit receipt. Having no job, pre-ONE, had a particularly strong effect in raising the time spent on benefit. However, unemployment effects are weaker here, while the effects of sickness/illness, pre-ONE, are stronger. Pay in the pre-ONE job was not significant in predicting wave two status, but here higher pay in that job is associated with reduced time claiming post-ONE.
- ONE: there are strong effects associated with ONE that were less apparent in the wave two benefit status models. However, there are fewer benefit area effects here.
- Date of entry to ONE: this was not significant in estimating wave two benefit receipt, but later entry is associated with a lower percentage of time on benefit in these models.
- Household effects: marriage and divorce are both associated with lower percentages of time on benefits in the fullest models, whereas they were not significant for wave two benefit status. The significant effects of children on benefit receipt twelve months after their claim for benefit are largely absent here.
- Long-standing illness: whereas long-standing illness was associated with higher probabilities of out-of-work benefit receipt twelve months after their claim for benefit only where the respondent said the illness affected their work, here long-standing illness raises the time on benefits, regardless of the individual's assessment of its impact on their work prospects.
- Attitudes to work: very positive attitudes significantly lower percentage of time on benefit, but they are not significant for benefit status twelve months after their claim for benefit.

Table 3.16 indicates the significance of variables, and the direction of effects, across all three outcomes for the sick and disabled, summarising the models in Appendix A. There are some differences in the impact of variables across the three outcomes, but the similarity is quite striking, particularly for the wave two outcomes. However, it is also evident from the discussion above and Table 3.16 that influences on early and later benefit outcomes differ, and this needs to be borne in mind in constructing profiling models. We reiterate the point made earlier that, just because a variable is statistically significant does not mean it is required for profiling purposes because what matters is the variable's ability to discriminate across individuals in ranking them according to their predicted work and benefit outcomes.

Table 3.17 shows how good the OLS models are at targeting treatment on the right clients, by which we mean those who go on to spend a higher percentage of their time on benefits. In the case of the 30 per cent cut-off, individuals are identified as 'correctly treated' if they are in the top 70 per cent of clients in terms of the percentage of time they spend claiming out-of-work benefits, and their predicted time on out-of-work benefits is also among the top 70 per cent of clients. They are wrongly treated if their predicted time on out-of-work benefits is in the highest 70 per cent of clients but, in fact, they are among the 30 per cent with the lowest percentage of time spent on out-of-work benefits. They are wrongly denied if their predicted time on out-of-work benefits is within the lowest 30 per cent of clients, but their actual time claiming is in the highest 70 per cent of clients. Similar calculations are made for the 50 per cent and 70 per cent cut-offs.

Table 3.16 Guide to significance of variables in sick and disabled models

	Without a job at wave 2	On OOW benefit at wave 2	Percentage time claiming, ONE-31/12/02
Female	+	ns	ns
Age (ref: <25 yrs)	+	+	+
Qualifications (ref: none)	-	-	-
Numeracy problems	+	+	+
Housing tenure (ref: owner occupation)	+ if renting from local authority, privately, or if 'other' tenure	+ if renting, all types, or if 'other' tenure	+ if renting, living in institution or 'other' tenure
Marital status (ref: single)	- widowed or divorced	- married or cohabiting	- married, cohabiting or divorced
Number of children (ref: one)	- 2 children	- no children or 2 children	- two children
Benefit history in 2 yrs pre-ONE	- if in-work benefit	+ if OOW benefit	+ OOW benefit or combination of OOW and in-work benefit
% time working 16+ hrs in 2 yrs pre-ONE	-	-	-
% time working <16 hrs in 2 yrs pre-ONE	-	+ if <50% time, - if 50% or more	-
Unemployed in 2 yrs pre-ONE	-	-	-
Any illness in 2 yrs pre-ONE	ns	-	-
Any education in 2 yrs pre-ONE	ns	-	-
Any sickness in 2 yrs pre-ONE	ns	ns	+
Any 'other' activity in 2 yrs pre-ONE	-	-	ns
Occupational class in pre-ONE job (ref: professional/intermediary)	ns	ns	+ if no previous job
Net pay in pre-ONE job (ref: <£100 pw)	u-shaped	ns	- if higher wage
Date of ONE eligibility	ns	ns	-

Continued

Table 3.16 Continued

	Without a job at wave 2	On OOW benefit at wave 2	Percentage time claiming, ONE-31/12/02
TTWA benefit stocks and flows	- with higher % disabled claimants; + with higher % lone parents	- with higher % disabled claimants; + with higher % lone parents	ns
General health (ref: poor)	-	-	-
Long-standing illness (ref: none)	+ if says affects work	+ if says affects work	+ whether says affects work or not
Mental disability	+	+	+
Care responsibilities (ref: yes, affects work)	- if caring but does not affect work	- if no care or caring does not affect work	- if no care or caring does not affect work
Licence (ref: no licence, no vehicle access)	- if licence and access	- if licence, whether access or not	- if licence and access
Number of household workers (ref: none)	-	-	-
Attitudes to working (ref: very negative)	-	-	-

Notes: (1) +/- denote positive and negative significant effects at 95 per cent confidence level or above in at least one of the parsimonious, middling or full models. ns denotes non-significance (2) Variables that are never significant are excluded from this table (3) Area dummies and ONE pilot dummies both had significant effects but are not shown in the table (4) Full tables are appended in Appendix A

Correct prediction rates (column 1) for the 30 per cent and 50 per cent cut-off are similar to those for the wave two benefit status models reported in Table 3.12, though at the 50 per cent cut-off, the wrong treatment rate is higher using this model, and the wrong denial rate lower. However, what is most striking about the comparison with Table 13 is the much better correct prediction rate at the 70 per cent cut-off, that is, for carefully targeted treatment on offer to only 30 per cent of the population. The correct prediction rate is roughly 10 percentage points higher that the model estimating percentage of time on benefit than it is for the model estimating benefit status twelve months after their claim for benefit. This gain is made through a substantial reduction in the wrong denial rate, which falls by around 17 percentage points. This is offset, however, by an increase in the wrong treatment rate of around seven percentage points. In other words, the time on benefit models reduce the number of false negatives but increase the number of false positives. The percentage of time on benefits model performs better than the status twelve months after their claim for benefit model for the 70 per cent cut-off, in part because the continuous dependent variable allows the model to discriminate better across claimants than probabilities based on a binary outcome. This finding mirrors that in the U.I. literature for the U.S., where using the information on the fraction of benefits exhausted allows better predictions than just a binary indicator for benefit exhaustion.

Table 3.17 Success in targeting treatment at different cut-offs for treatment allocation using predicted percentage of time claiming out-of-work benefits between ONE eligibility and 31 December 2002

	Correctly predicted	Correctly treated	Wrongly predicted	Wrongly treated
30% cut				
M(2)	68	54	16	16
M(6)	76	58	12	12
50% cut				
M(2)	65	32	18	17
M(6)	70	34	15	14
70% cut				
M(2)	68	19	10	22
M(6)	69	19	10	21

Note: treatment allocation in validation sample. 30 per cent cut = time on OOW benefit prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = time on OOW benefit prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = time on OOW benefit prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on OLS model.

Table 3.18 presents the information in Table 3.17 in a different way. Row 1 shows the wrong prediction rate rises with more targeted treatment, but not so steeply as in the case of the wave two benefit status models (see Table 3.13). However, as we move to a more targeted treatment offered to 50 per cent, the wrong prediction rate among those predicted not to need treatment declines, whereas it rises among those predicted to need treatment. These findings contrast with those for wave two benefit status. Row 4 uses as its base the clients whose actual time on benefits is below the rate entitling them to treatment. In 40 per cent of these cases, their predicted time on benefit is higher than the 30 per cent cut-off, resulting in unnecessary treatment. This figure falls progressively with more targeted treatment. Row 5 uses as its base the clients whose actual time on benefits is above the rate entitling them to treatment. With a 30 per cent cut-off, over four-fifths of these clients are actually treated, but this falls to a half with a 70 per cent cut-off.

Table 3.18 Prediction rates at different cut-offs for treatment allocation using predicted percentage of time on out-of-work benefits, ONE eligibility – 31 December 2002

	30% cut	50% cut	70% cut
Percentage all predictions wrong	24	30	31
Percentage all negative predictions wrong	40	28	30
Percentage all positive predictions wrong	17	29	34
Percentage those with time on benefits below cut-off who are wrongly treated	40	30	17
Percentage those with time on benefits above cut-off who are correctly treated	82	71	48

Notes: prediction rates in validation sample based on M(6) results presented in Table 3.17

We can draw the following inferences from the analysis presented above:

- Profiling outperforms random allocation of the treatment because the models are good at ranking individuals according to the percentage of time they spend claiming out-of-work benefits.
- The 'full' model outperforms the other models, indicating that there is value to the collection of these additional data. Some gains are also made by moving from the most parsimonious to the 'middling' models.
- The OLS estimator marginally outperforms the tobit estimator.
- Influences on early and later benefit outcomes differ, and this needs to be borne in mind in constructing profiling models.
- There are no unambiguous advantages to using percentage of time spent claiming rather than wave two benefit status as the profiling variable: the relative performance of profiling on these two outcomes using identical models differs with the cut-off point chosen to allocate treatment. With a 70 per cent cut-off, the correct prediction rate is higher when using percentage of time spent claiming, but profiling based on wave two benefit status results in slightly better profiling with 30 per cent and 50 per cent cut-offs.

4 Analysis and results for lone parents

- Just over 72 per cent of lone mothers (and 72.5 per cent of all lone parents) were out-of-work 12 months after approaching DWP to make a claim for out-of-work benefits; 66 per cent of lone mothers (67 per cent of all lone parents) were claiming out-of-work benefits at the 12 month point; 35 per cent of lone mothers spent all of the 30 months since making the claim on out-of-work benefits, the mean percentage of time spent claiming being 67 per cent.
- Profiling outperforms random allocation of the treatment.
- The out-of-work benefit status models perform better than the out-of-work labour market status models because the model generates fewer false negatives.
- Determinants of benefit and out-of-work status are similar but not identical. Determinants of benefit status at the 12 month point and over the 30 month period differ in a number of respects.
- The 'full' models outperform other models when profiling on out-of-work labour market status and benefit status 12 months after claiming but, in the case of the percentage of time claiming over 30 months, there are no gains to more extensive models.
- There is little to choose between functional forms but the logit estimator performs marginally better than the OLS and probit estimators when estimating status at the 13 month point, while the OLS outperforms the tobit in estimating time on benefits over the whole 30 months.
- Profiling lone parents with models devised for the sick and disabled produces poorer results than profiling lone parents with models devised specifically for lone parents.
- Models for all lone parents perform a little better than those for lone mothers only.
- Sensitivity analyses made little difference to the results, although there were differences in performance when separate models were estimated for younger and older lone mothers.
- Profiling models for the sick and disabled generally performed better than those for the lone mothers.

This section reports analysis and results for lone parent clients in the ONE database. For the purposes of the ONE evaluation, a client is classified as a lone parent if they initially approached the Department about a lone parent benefit – whether or not they went on to claim that benefit, and regardless of their marital status by the time of the first survey interview. 4,854 were interviewed at the first interview and 3,578 were interviewed at the second interview. Although we report some headline results for all lone parents, the bulk of the analysis focuses exclusively on lone mothers, who made up 93 per cent of ONE's lone parents. There were 4,503 lone mothers in the database, including 3,334 who were interviewed at the second interview.

4.1 Outcomes for lone parents

Table 4.1 shows the labour market status of lone parent respondents twelve months after their claim for benefit: 27.5 per cent were doing some paid work at that point – an employment rate slightly lower than that for the sick and disabled (at 30 per cent). The remaining 72.5 per cent were distributed across the categories emboldened in the table. The rate is similar for all lone parents (column 1) and lone mothers (column 2). A little over half were looking after the home.

Table 4.1 Labour Market Status twelve months after their claim for benefit

	Weighted column percentage, all lone parents	**Weighted column percentage, lone mothers**
30+ hours paid work	8.0	7.3
16-29 hours paid work	13.4	14.1
<16 hours paid work	6.1	6.3
Full-time education	**5.6**	**5.8**
Government scheme	**0.3**	**0.3**
Unemployed	**8.6**	**7.8**
Looking after home	**51.8**	**52.5**
Temporarily sick or injured	**2.6**	**2.3**
Permanently sick or disabled	**2.5**	**2.4**
Not working, other reasons	**1.1**	**1.1**

Base unweighted: =3,577 for all lone parents and 3,333 for lone mothers. There was one case where labour market status could not be accurately determined

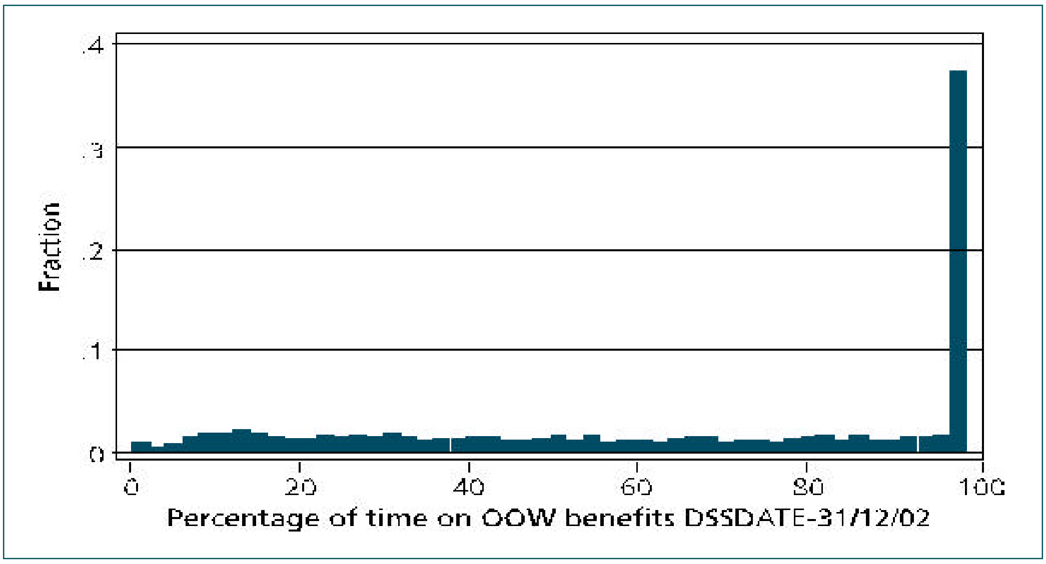
Table 4.2 identifies what out-of-work benefits lone parents said they were receiving twelve months after their claim for benefit. Sixty-seven per cent of respondents received at least one of the six out-of-work benefits identified, as did 66 per cent of lone mothers. This percentage is almost identical to that for the sick and disabled (Table 3.2) but, in contrast to the sick and disabled where one-third received Income Support, Income Support accounts for nearly all claims among lone parents. Sixty-one per cent of respondents were in receipt of a single out-of-work benefit, with six per cent receiving two or three.

Table 4.2 Out-of-work benefits received twelve months after their claim for benefit

	Weighted cell percentage, all lone parents	Weighted cell percentage, lone mothers
Income Support	63.0	62.9
Jobseekers' Allowance	2.8	2.4
Widow's Benefit	1.0	1.0
Incapacity Benefit	3.0	2.7
Invalid Care Allowance	2.9	2.9
Severe Disablement Allowance	0.3	0.4
Any of the above	66.7	66.1

Note: unweighted N=3,576 for all lone parents and N=3,332 for lone mothers. There were 2 cases whose benefit status could not be accurately determined

Figure 4.1 Percentage of time spent on out-of-work benefits between ONE eligibility and 31 December 2002, all lone parents



We were able to match 94.7 per cent (4,595 out of 4,854) of the lone parent clients who responded at wave one to administrative benefit records. Over one-third (35 per cent) of wave one respondents had spent all of their time on one or more of the out-of-work benefits qualifying clients for ONE (JSA, IS, IB, ICA, SDA, WB or BB), with the remainder spread fairly evenly across the rest of the distribution (Figure 4.1). The pattern is identical for lone mothers only. Forty-six per cent of the sick and disabled had spent all of their time on out-of-work benefits. Thus, although a similar percentage of lone parents and sick and disabled clients were on out-of-work benefits twelve months after their claim for benefit, there is more movement off benefit among lone mothers than there is among the sick and disabled.

4.2 Models used in profiling lone parents

For the bulk of our analysis of lone mothers we used the model specifications described in Figure 4.2: it shows the variables used in the parsimonious (column 1), middling (column 2) and full models (column 3). The models used for all lone parents, which are not shown, differ in some respects from the lone mother models because variables differ in their impact on lone mothers and lone fathers.

Figure 4.2 Variables used in models profiling lone mothers[20]

Models (1)-(2)	Models (3)-(4) – as (1) and (2) plus:	Models (5) and (6) – as (3) and (4) plus:
Demographics 7 education dummies 6 actual marital status dummies 5 dummies for number of children 5 housing tenure dummies 5 dummies for age of youngest child **Work history in 2 years pre-ONE** 6 dummies for % time working 16+ hours per week 3 dummies for % time working 1-15 hours per week If ever worked before 5 dummies identifying any time in 2 year before claim in the following states: – temporarily or permanently sick/disabled – unemployed – full-time education – training – other (eg. looking after home) **Area** 6 dummies for ONE/control areas, OR 24 benefit area dummies	**Demographics** 8 lone parent's age dummies Ethnicity – White If numeracy problems If literacy problems If vocational education **Work history in 2 yrs pre-ONE** 6 net pay in pre-ONE job dummies 6 social class in last pre-ONE job dummies **Benefit history in 2 yrs pre-ONE** If ever received out-of-work benefits only If received in-work benefits only If received both out-of-work and in-work benefits If received no benefits **Area** TTWA benefit stocks/flows for unemployment, lone parents, sick and disabled	**Demographics** 3 dummies for general health in last year 3 dummies for long-standing illness Mental disability dummy 3 care responsibility dummies If possess telephone 3 dummies for vehicle access and licence 3 dummies for number of household workers 5 dummies for work attitudes 3 dummies for a regular income (other than earnings and benefits) 4 dummies for who lives with

[20] The models used to profile out-of-work benefit status models at wave two and time spent claiming between ONE eligibility and 31 December 2002 were identical, except they split the 'temporarily or permanently sick/disabled' dummy into two dummies identifying sickness and disability and illness.

In addition, to allow comparisons with the analysis for the sick and disabled, we ran some analyses using specifications that are identical to those for the sick and disabled, as described in Figure 3.1. Analyses for the three outcomes described in Section 4.1 are presented in turn below. The sensitivity analyses undertaken are identical to those undertaken for the sick and disabled, except:

- we do not present separate models for men;
- separate analyses by age distinguish between lone mothers aged below 35 years and those aged 35 or more, a cut-off more appropriate to lone mothers' age distribution than the 45-year threshold used for the sick and disabled;
- exploration of the impact of ward-level deprivation includes consideration of the child poverty and access to services indices which, *a priori*, one might expect to be important in the case of lone mothers.

4.3 Results

4.3.1 Without a job twelve months after their claim for benefit

Table 4.3 shows the mean proportion of lone mothers who were without paid work at the wave two survey interview in each quintile of the predicted distribution of out-of-work probabilities. It does so for the logit, probit and OLS specifications of Models (2) and (6), namely the most parsimonious and fullest models containing the 24 area dummies. Recall that, in the raw data, 72 per cent of the sample were out of work at that stage, roughly one year after ONE eligibility. If ranked according to actual outcomes, the proportions in Q5-Q3 would be 1, the proportion in Q2 would be .6 and the proportion in Q1 would be zero – as was the case for the sick and disabled. Ranking claimants according to their predicted probability of being out-of-work twelve months after their claim for benefit, depending on the model, 88 – 92 per cent of the highest quintile actually go on to be out of work, compared with 46 – 49 per cent of those in the lowest quintile of predicted probabilities. Thus, despite a very similar distribution on the outcome variable, these dedicated lone mother models do not seem to perform as well the models for the sick and disabled, reported in Table 3.3. The proportions predicted to be out of work in the lowest quintile are substantially higher in the case of the lone mothers, especially in the case of Model (6).

Table 4.3 Comparison of proportions out of work twelve months after their claim for benefit for lone mothers, by quintiles of predicted out-of-work status for logit, probit and OLS

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Q5	0.88	0.92	0.88	0.92	0.89	0.91
Q4	0.83	0.84	0.82	0.84	0.80	0.86
Q3	0.79	0.77	0.79	0.76	0.82	0.74
Q2	0.70	0.70	0.71	0.69	0.69	0.69
Q1	0.48	0.46	0.48	0.47	0.49	0.47

Note: all models run on 70 per cent sample and results based on 30 per cent validation sample

As in the case of the sick and disabled:

- allocation through profiling is preferable to random allocation of treatment since, using the predictions from any of the estimation methods, profiling does a much better job at identifying which clients are likely to remain out of work a year later;

- the full models do a better job than the parsimonious models at identifying those with the lowest out-of-work probabilities, as indicated by the lower proportions out of work in the lowest predicted quintiles derived from full models relative to parsimonious models;
- there is little to choose between the performance of the different functional forms.

Table 4.4 compares the predictive performance of the logit, probit and OLS using Models (2), (4) and (6). It presents differences in the proportion predicted out of work between the top and the bottom of the distribution of predicted probabilities.

Table 4.4 Differences in proportion predicted out of work, by quintiles of the predicted probability distribution for lone mothers

	Logit			Probit			OLS		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	0.35	0.37	0.44	0.34	0.36	0.43	0.31	0.32	0.37
T60%-B40%	0.30	0.31	0.36	0.30	0.31	0.35	0.28	0.29	0.33
T40%-B60%	0.27	0.28	0.31	0.27	0.28	0.31	0.27	0.28	0.31
T20%-B80%	0.25	0.26	0.28	0.26	0.26	0.28	0.28	0.29	0.33
Average dif.	0.29	0.31	0.35	0.29	0.30	0.34	0.29	0.30	0.34

Note: models with 24 area dummies; T=top, B=bottom; estimation sample=2333; validation sample = 1000

As in the case of the sick and disabled, the logit outperforms the probit and OLS models, though the differences are not great. Again, as in the case of the sick and disabled, there is evidence that the OLS is better at predicting throughout the distribution: in the logit and probit models mean differences decline as one moves from row 1 to row 4, something that does not happen in the case of the OLS. Comparing the average differences in predicted outcomes across Models (2), (4) and (6), there is almost no gain moving from (2) to (4), but there are clear gains in profiling with Model (6), as indicated by an average difference of four to six percentage points over the other models.

Table 4.5 Comparison of average differences in predicted out-of-work probabilities

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Av. dif. For preferred lone mother models	.29	.35	.29	.34	.29	.34
Av. dif. For preferred lone parent models	.30	.36	.30	.36	.30	.35
Av. dif. for all lone parents with sick and disabled model specification	.29	.34	.29	.34	.28	.33
Av. dif. For sick and disabled	.38	.45	.37	.45	.36	.43

Using the average difference criterion, Table 4.5 compares the performance of the parsimonious and full models for lone mothers, all lone parents and the sick and disabled. The first row is taken from the last row of Table 4.4. Row 2 shows the performance of models designed for, and run on, all lone parents perform slightly better. As one might expect, row 3 shows profiling all lone parents with models designed for the sick and disabled reduces performance, confirming the value in devising profiling instruments dedicated to different client groups. Row 4 replicates the average differences from the sick and disabled models presented in Table 3.4, and shows that, for the out-of-work outcome that is similarly distributed for the two client groups, the profiling models for the sick and disabled perform better than those for lone parents and lone mothers.

Table B.2 presents Models (1) – (6) using the logit estimator to illustrate which variables in the models are statistically significant (Table B.1 gives the meaning of variable labels used in the lone mother models). In the most parsimonious models (1) and (2), probabilities of being out of work twelve months after their claim for benefit fall with better qualifications, owner occupation, the ageing of the youngest child to school leaving age, and time spent in full-time and part-time employment in the two years prior to ONE, and even before that. The number of dependent children and marital status are not significant. These results hold with the addition of further variables in Models (3) – (4), although the qualification effects weaken and some marital status effects emerge with the probabilities of being out of work falling among married and separated lone mothers relative to single lone mothers. Most of the additional variables included in Models (3) and (4) relating to age, ethnicity, numeracy, literacy, social class and pay in last job before ONE, and area-based benefit stock and flow information are not statistically significant. The exception is claiming out of work benefits in the two years before ONE: this raises the probability of being out of work twelve months after their claim for benefit. The out-of-work benefit effects and the marriage effect disappear in Models (5) and (6) with the addition of variables that may (or may not) be endogenous. Probabilities of being out-of-work fall with other household workers, positive work attitudes, having a licence and access to a vehicle, and having a telephone. Having a long-standing illness affecting one's ability to work and sources of income other than child support or a pension, both raise the probabilities of being out-of-work by wave two.

Table 4.6 takes the logit Models (2) and (6) discussed above and identifies the percentages in the validation sample who are correctly predicted (column 1), those who are correctly treated (column 2), those who are wrongly treated (column 3), and those who are wrongly denied access to treatment (column 4) at three different cut-off points for treatment. As was the case for the sick and disabled (Table 3.5), the correct prediction rate is highest with a 30 per cent cut-off, as one would expect since the 70 per cent treatment group coincides with the percentage of lone mothers who were actually out of work twelve months after their claim for benefit. The correct prediction rate is poorest with the 70 per cent cut-off, that is, with careful targeting. This was also the case for the sick and disabled. However, the correct prediction rate is appreciably lower for the lone mothers than it is for the equivalent profiling model for the sick and disabled (10 percentage points lower in the case of Model (2) and seven percentage points lower in the case of Model (6)).Model specification makes some difference, with the full model outperforming the parsimonious model at all cut-off points, though the differences are not large. Again, as in the case of the sick and disabled, as the target group for treatment rises, so the percentage of the eligible group who are wrongly treated rises, while the percentage who are wrongly denied falls.

Table 4.6 Success in targeting treatment at different cut-offs for treatment allocation using out-of-work probabilities twelve months after their claim for benefit

	Correctly predicted	Correctly treated	Wrongly treated	Wrongly denied
30% cut				
M(2)	70	57	13	16
M(6)	73	59	12	15
50% cut				
M(2)	60	42	8	32
M(6)	64	44	6	30
70% cut				
M(2)	48	26	4	48
M(6)	51	28	3	46

Note: treatment allocation in validation sample. 30 per cent cut = OOW prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = OOW prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = OOW prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative.

Predictions based on logit model.

The figures in Table 4.6 are percentages of the whole validation sample. In Table 4.7 we express the same information in a different fashion to shed further light on the success of the models in targeting treatment. The first row shows wrong prediction rates rise with more targeted treatment. The second row shows the wrong prediction rate is particularly high among those predicted not to need treatment. With a 30 per cent cut-off, over half those predicted not to need treatment are actually out of work twelve months after their claim for benefit. This rises to 67 per cent with a 70 per cent cut-off. These figures are around 10 percentage points higher than in the case of the sick and disabled models (see Table 7). On the other hand, few of those predicted to need treatment actually find a job – 17 per cent in the case of the 30 per cent cut-off, falling to 10 per cent with a 70 per cent cut-off (row 3). These figures compare favourably to those for the sick and disabled.

Table 4.7 Prediction rates at different cut-offs for treatment allocation using out-of-work probabilities twelve months after their claim for benefit

	30% cut	50% cut	70% cut
Percentage all predictions wrong	27	36	49
Percentage all negative predictions wrong	52	61	67
Percentage all positive predictions wrong	17	12	10
Percentage in work wrongly treated	46	23	12
Percentage out of work correctly treated	80	59	38

Notes: prediction rates in validation sample based on M(6) results presented in Table 4.7

Using actual out-of-work status twelve months after their claim for benefit as its base, row 4 shows nearly half (46 per cent) of those in work twelve months after their claim for benefit would have been wrongly treated as a result of their profiling prediction where 70 per cent of the sample is treated. This falls to 12 per cent where only 30 per cent of the sample are treated. Finally, row 5 shows four-fifths of those who actually went on to be out of work twelve months after their claim for benefit would have been treated following profiling with a treatment aimed at 70 per cent of the sample. This falls to 38 per cent in a smaller programme where only 30 per cent are treated. This final set of figures show an accuracy rate that is not quite as good as the sick and disabled models.

Having presented our basic results for this outcome we turn to our sensitivity tests, which are virtually identical to those reported for the sick and disabled. As noted in the analysis of the sick and disabled, Models (1) and (5) are used to present results for these sub-sample analyses because these avoid use of the 24-category benefit area variable which, when sample sizes fall, results in the rejection of some cases due to perfect prediction of the outcome in benefit areas with small cell sizes. Results were as follows:

- Running profiling for the English sub-sample with and without deprivation indices made very

[21] Of the 4,854 lone parents in the ONE data, 259 had no identifiable claimant administrative records. A further 494 were linked to administrative data but had no ward identifier that could be matched to the deprivation data. In 484 cases this was because the client lived in Scotland or Wales. Thus, 4,101 of the 4,854 lone parents had ward identifiers linking to the deprivation data. The use of ward-level deprivation data reduced the sample for analysis of wave two out-of-work status by 1,107 cases to 2,994. The analysis here is confined to the 2,784 who were lone mothers. We tested the impact of multiple deprivation, employment deprivation, income deprivation and child poverty.

little difference to the profiling diagnostics, even though some of the deprivation measures were statistically significant in the models.[21]

- Re-estimating models excluding benefit area variables resulted in a small decline in average differences of two percentage points in logit parsimonious and full models. However, correct prediction rates at the 30 per cent, 50 per cent and 70 per cent cut-offs are virtually identical with and without area variables included.

- Switching to an 80:20 split between the estimation and validation samples makes very little difference to differences in out-of-work predictions across quintiles of the predicted probabilities and the percentage of correct predictions.

- Confining the sample to those respondents who said at the wave one interview that they had made a claim for benefits (dropping 246 non-claimants) resulted in a one percentage point decline in average differences in the parsimonious and full models. Correct prediction rates with a 30 per cent cut-off dropped by one percentage point in the case of the parsimonious model and two percentage points with the full model. However, correct prediction rates were one to two percentage points higher for the claimant-only sample than the whole sample at the 70 per cent cut-off. Overall, then, there is little to choose between the samples in terms of profiling performance.

- Running separate profiling models by age produced marked differences in the predictive power of the profiling models. Average differences were 11 percentage points higher for lone mothers aged 35 or more than they were for lone mothers aged under 35. Correct prediction rates were similar at the 30 per cent cut-off but, where treatment was confined to 30 per cent of the sample, the model for the older age group performed much better (Table 4.8). The reason for the difference is clear. The employment rate for older lone mothers is considerably higher (33 per cent compared to 25 per cent), the chief reason being the high incidence of younger lone mothers with a child aged under three (50 per cent among mothers aged under 35 compared with 11 per cent among mothers aged 35+). The greater variance in the older lone mothers sample makes it easier for the profiling model to differentiate across lone mothers when predicting outcomes. In addition, the employment rate happens to coincide with the entitlement level when treatment is allocated with a 70 per cent cut-off.

Table 4.8 Diagnostics for out-of-work status twelve months after their claim for benefit, by age

	Less than 35 years		35+ years	
	M(1)	M(5)	M(1)	M(5)
Average difference	.25	.32	.36	.43
Percentage correct predictions (30% cut-off)	68	70	70	70
Percentage correct predictions (70% cut-off)	46	48	57	58

Logits, with 70% estimation sample, 30% validation sample

The inferences we draw from the analysis for lone mothers are as follows:

- Profiling outperforms random allocation of the treatment.

- The 'full' model outperforms the other models.

- There is little to choose between functional forms but the logit estimator performs marginally better than the OLS and probit estimators.

- Profiling lone parents with models devised for the sick and disabled produces poorer results than profiling lone parents with models devised specifically for lone parents.

- Models for all lone parents perform a little better than those for lone mothers only.
- Sensitivity analyses made little difference to the results, except in the case of the split by age where profiling for those aged 35+ performed better than profiling for younger lone mothers.
- These conclusions are very similar to those for the sick and disabled, although the profiling models for the sick and disabled generally performed better than those for the lone mothers.

4.3.2 Claiming out-of-work benefit twelve months after their claim for benefit

Identical analyses were undertaken to predict the probability of claiming one or more out-of-work benefits at the second wave interview. As shown in Table 4.2, around two-thirds of wave two respondents said they were in receipt of these out-of-work benefits. In fact, 34 lone mothers said they were in receipt of out-of-work benefits and in paid work of 16 hours or more, so we tested the sensitivity of results to the exclusion of this group.

Recall that in the raw data 66 per cent of lone mothers were claiming out-of-work benefit at that stage. If ranked by quintile according to actual wave two status, the proportions in Q5 – Q3 would be 1, the proportion in Q2 would be .3, and the proportion in Q1 would be zero.

Table 4.9 compares the proportion of lone mothers claiming out-of-work benefits twelve months after their claim for benefit ranked according to their predicted probability of benefit receipt using logit, probit and OLS Models (2) and (6). Depending on the model, 86 – 88 per cent of the highest quintile actually go on to claim out-of-work benefit, compared with 31 – 36 per cent of those in the lowest quintile of predicted probabilities. All models perform better than random allocation, where the proportion claiming in each quintile would fluctuate around .66. It is notable, however, that the parsimonious Model (2) does a poor job in correctly allocating individuals between Q3 and Q4, as indicated by the similar claimant rates for those two quartiles, regardless of functional form. The full models do a much better job at ranking individuals according to their future benefit status. There is little to choose between the performance of the different functional forms.

Table 4.9 Comparison of proportions claiming out-of-work benefits twelve months after their claim for benefit for lone mothers, by quintiles of predicted out-of-work status for logit, probit and OLS

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Q5	0.88	0.87	0.88	0.87	0.86	0.86
Q4	0.72	0.82	0.73	0.80	0.75	0.81
Q3	0.75	0.75	0.75	0.77	0.75	0.77
Q2	0.57	0.53	0.56	0.54	0.57	0.54
Q1	0.36	0.32	0.36	0.32	0.36	0.31

Note: all models run on 70 per cent sample and results based on 30 per cent validation sample

Table 4.10 compares the predictive performance of the logit, probit and OLS using Models (2), (4) and (6). Comparing across functional forms, the average differences in predicted outcomes are very small, and there is nothing to choose between the logit and probit estimators. In each case, the most parsimonious model, M(2), performs reasonably well, there are small gains in moving from M(2) to

M(4), and further gains moving to the fullest model, M(6). These average differences are better than those for the equivalent out-of-work labour market status models reported in Table 4.4.

Table 4.10 Differences in proportion predicted to receive out-of-work benefits, by quintiles of the predicted probability distribution

	Logit			Probit			OLS		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	0.37	0.39	0.49	0.37	0.38	0.48	0.34	0.35	0.44
T60%-B40%	0.31	0.34	0.42	0.31	0.33	0.41	0.29	0.31	0.38
T40%-B60%	0.29	0.30	0.36	0.29	0.30	0.36	0.28	0.30	0.35
T20%-B80%	0.28	0.30	0.33	0.29	0.30	0.34	0.30	0.31	0.36
Average dif.	0.31	0.33	0.40	0.31	0.33	0.40	0.30	0.32	0.38

Note: models with 24 area dummies; T=top, B=bottom; estimation sample=2331; validation sample = 1000

Using the average difference criterion, Table 4.11 compares the performance of the parsimonious and full models for lone mothers, all lone parents and the sick and disabled. The first row is taken from the last row of Table 4.10. Row 2 shows models designed for, and run on, all lone parents perform very similarly to those run on lone mothers only. Row 3 shows profiling all lone parents with models designed for the sick and disabled reduces performance, again confirming the value in devising profiling instruments dedicated to different client groups. Row 4 replicates the average differences from the sick and disabled models presented in Table 3.11. It shows that, for this out-of-work benefit outcome, which is similarly distributed for the two client groups, the profiling models for the sick and disabled perform better than those for lone parents and lone mothers.

Table 4.11 Comparison of average differences in predicted out-of-work probabilities

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Av. Dif. for preferred lone mother models	.31	.40	.31	.40	.30	.38
Av. Dif. for preferred lone parent models	.30	.40	.30	.39	.29	.38
Av. dif. for all lone parents with sick and disabled model specification	.26	.38	.26	.38	.25	.37
Av. Dif. for sick and disabled	.32	.43	.32	.43	.32	.43

Table B.3 presents Models (1) – (6) using the logit estimator to illustrate which variables in the models have a significant impact predicting out-of-work benefit status twelve months after their claim for benefit. Effects are very similar to those presented in Table B.2 for out-of-work labour market status, with some differences. For example, part-time working in the two years before ONE is no longer significant, whereas periods of sickness or education in that period become significant. Having a telephone is no longer significant. On the other hand, having no child becomes significant, as does general health, and carer responsibilities. Marital status becomes more pronounced in its effects, while the effects of education and age of youngest child differ somewhat from their significant effects in the job status models. As was the case with the sick and disabled, the determinants of benefit status differ somewhat from the determinants of labour market status.

Table 4.12 shows how good the profiling models are at targeting treatment on those who go on to claim out-of-work benefits twelve months after their claim for benefit. The results are based on logit Models (2) and (6) and are thus comparable to those presented for out-of-work labour market status in Table 4.6. The correct prediction rates (column 1) for benefit receipt are better than those for labour market status, especially at the 70 per cent cut-off. This is because the proportions wrongly denied treatment are a little lower than in the case of the out-of-work labour market predictions, and this difference is only partly off set by higher proportions wrongly treated. Nevertheless, the correct prediction rates remain below those for the equivalent sick and disabled models reported in Table 3.12.

Table 4.12 Success in targeting treatment at different cut-offs for treatment allocation using out-of-work benefit receipt probabilities twelve months after their claim for benefit

	Correctly predicted	Correctly treated	Wrongly treated	Wrongly denied
30% cut M(2) M(6)	7174	5455	1715	1211
50% cut M(2) M(6)	6567	4142	109	2524
70% cut M(2) M(6)	5456	2526	54	4140

Note: treatment allocation in validation sample. 30 per cent cut = OOW benefit receipt prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = OOW benefit receipt prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = OOW benefit receipt prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on logit model.

Table 4.13 Prediction rates at different cut-offs for treatment allocation using out-of-work benefit receipt probabilities twelve months after their claim for benefit

	30% cut	50% cut	70% cut
Percentage all predictions wrong	26	35	44
Percentage all negative predictions wrong	37	48	57
Percentage all positive predictions wrong	21	18	13
Percentage in work wrongly treated	44	26	12
Percentage out of work correctly treated	83	64	39

Notes: prediction rates in validation sample based on M(6) results presented in Table 32

Table 4.13 row 1, which presents the information in Table 4.12 in a slightly different way, confirms the superiority of the model in profiling using the out-of-work benefit outcome as opposed to labour market status, at least when treatment is confined to 30 per cent of the sample (compare the last column in row 1 with the same cell in Table 4.7. The difference is driven by a lower rate of wrong predictions among the negative predictions, as a comparison of row 2 in the two tables indicates).

Sensitivity tests revealed the following:

- The exclusion of the small number of lone mothers claiming out-of-work benefits and working 16 or more hours per week made virtually no difference to the predictive accuracy of the models as measured in average differences and correct prediction rates.
- The addition of ward-level deprivation indices has no effect on the predictive accuracy of the models.
- Average difference and correct prediction rate diagnostics indicated models run on claimants only (that is, those saying they were in receipt of one or more out-of-work benefits at wave one) performed similarly to those run on the whole sample.

- Running the analysis on a random 80 per cent of the sample and validating it on a 20 per cent random sample had little effect on the profiling diagnostics.
- Splitting the lone mother sample by age, correct prediction rates were higher for the under-35s sample, whether using a parsimonious model (where the difference was three percentage points) or the full model (where the difference was two percentage points). At the 70 per cent cut-off, the parsimonious model produced a better correct prediction rate for under-35s than for those aged 35+ (by two percentage points), but the full model was better at correctly predicting for the older age group (by four percentage points).

We can infer the following from the analysis presented above:

- The predictive power of profiling models for out-of-work benefit status twelve months after their claim for benefit was better than that for out-of-work labour market status twelve months after their claim for benefit in terms of correct prediction rates and average differences because the benefit claiming model generated fewer false negatives.
- Determinants of benefit and out-of-work status are similar, but differ in some respects, and the lone mothers' models predict better for the lone mothers than the sick and disabled models, confirming the need to develop dedicated profiling tools for different client groups and across outcomes.
- Results were broadly similar when performing sensitivity tests, although there were differences in performance when separate models were run by age of lone mother.

4.3.3 Time claiming out-of-work benefits after ONE

In this section, we turn to our third dependent variable, namely the percentage of time lone mothers spent on out-of-work benefits between ONE eligibility and 31 December 2002. All but two of the lone parent clients became eligible for ONE in June or July of 2000, so the percentage is calculated over a period of around two and a half years.

Table 4.14 Percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002, by quintiles of predicted time claiming benefits OLS and tobit

		OLS			Tobit		
Distribution in the data		**M(2)**	**M(4)**	**M(6)**	**M(2)**	**M(4)**	**M(6)**
Q5	1.0	.86	.85	.85	.86	.86	.85
Q4	.98	.77	.78	.78	.76	.76	.79
Q3	.78	.69	.67	.71	.69	.68	.68
Q2	.45	.56	.60	.57	.58	.60	.58
Q1	.16	.47	.45	.44	.46	.46	.45

Note: all models run on 70 per cent sample (N=2,979) and results based on 30 per cent validation sample (N=1,277)

There is bunching at the top end of this continuous variable, with 1,503 of the 4,256 lone mothers successfully matched to the benefit data spending all of their time since ONE eligibility on out-of-work benefits. Thus, as in the case of the sick and disabled clients, we test the sensitivity of our profiling on this outcome to the OLS and tobit functions, the latter taking account of the bunching of observations at the upper bound of the dependent variable.

Table 4.14 shows the percentage of time lone mothers spent claiming out-of-work benefits between

ONE eligibility and 31 December 2002. The overall mean time spent on out-of-work benefits in the data is 67 per cent (72 per cent for lone fathers). If ranked according to the actual time spent claiming in the raw data, all those in the top quintile and virtually all those in the second quintile have been claiming out-of-work benefits throughout, while in the third quintile, the mean percentage of time spent claiming is 78 per cent (column 1). Although high, these figures are lower than those for the sick and disabled. However, the mean is only 16 per cent in the lowest quintile, showing that there are some who spend very little time claiming.

Ranking clients according to their predicted percentage of time on out-of-work benefits since ONE eligibility, the mean percentage of time on benefit among the highest quintile is 85 – 86 per cent (depending on the model), compared with 44 – 47 per cent among those in the lowest quintile. The models do a reasonable job at ranking individuals according to future time on benefits, as indicated by the sizeable differences in mean actual outcomes across the predicted outcome distribution. Where clients are randomly assigned to quintiles, the mean percentage of time on benefits fluctuates around 70 per cent, so profiling is clearly preferable to random allocation of treatment. Comparing functional forms, there is little to choose between the performance of the tobit and the OLS. What is striking about the table is that, in contrast to all the analyses presented so far for the sick and disabled and lone parents, the full models perform no better than the middling and parsimonious models in ranking lone mothers by their future benefit outcomes.

Table 4.15 Differences in percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002, by quintiles of predicted distribution

	OLS			Tobit		
	M(2)	**M(4)**	**M(6)**	**M(2)**	**M(4)**	**M(6)**
T80%-B20%	27.5	29.1	32.0	26.6	28.3	31.4
T60%-B40%	23.7	24.7	28.0	22.3	23.5	26.7
T40%-B60%	22.5	23.5	27.1	20.7	21.8	24.9
T20%-B80%	23.7	24.9	29.1	21.2	22.2	25.2
Average dif.	24.4	25.6	29.1	22.7	23.9	27.0

Note: all models run on 70% sample (N=2,979) and results based on 30% validation sample (N=1,277); T=top; B=bottom

Table 4.15 compares the predictive performance of the OLS and tobit using Models (2), (4) and (6). It presents differences in the average predicted time on out-of-work benefits between the top and the bottom of the distribution of predicted percentage of time claiming.

Comparing the average differences in predicted outcomes across functional forms, the OLS estimator outperforms the tobit estimator for all three models. The predictive power of the models is not driven by 'success' in any particular part of the distribution. Comparing the average differences in predicted outcomes across OLS Models (2), (4) and (6), the most parsimonious model performs reasonably well, but there is some gain moving from (2) to (4), and further gains in profiling with Model (6), the average difference rising by 4.5 percentage points as we go from Model (2) to (6). As was the case for the sick and disabled, the models appear less discriminating than those estimating whether on benefits twelve months after their claim for benefit since, with similar mean scores for both variables, the average differences presented in Table 4.10 are larger than those presented in Table 4.15.

Table B.4 presents Models (1) – (6) using the OLS estimator to illustrate which variables in the models are statistically significant. The bullet points below comment on these results, comparing them to identical OLS models (not shown) estimating the probability of being in receipt of out-of-work benefits twelve months after their claim for benefit. The commentary focuses on results that differ from those discussed in the analysis of wave two benefit receipt:

- Age: in Models (3) and (4), those aged 20 – 34 spent less time claiming out-of-work benefits than lone mothers aged under 20, whereas age was only significant for wave two benefit status in Model (4) where those aged 20 – 24 had a lower probability of being on benefit than those aged under 20.
- Qualifications: degree-level and A-level qualifications reduce time on benefits in Models (1) to (6), and any qualifications reduce time on benefits relative to no qualifications in the parsimonious models. Qualifications at A-level or above were associated with lower probabilities of claiming out-of-work benefits twelve months after their claim for benefit, although the only effect that remained significant in Models (5) and (6) was the impact of A-levels.
- Numeracy problems: numeracy problems increased time on benefits in Models (3) and (4) but they are not significant in estimating wave two benefit receipt.
- Housing tenure: renters spend more time on benefits than home owners, but only the effect of private renting remains significant throughout, whereas all types of renting increased the probability of claiming benefits twelve months after their claim for benefit.
- Children: time spent on benefits declined with the age of the youngest child but number of children was not significant. Similar effects were apparent twelve months after their claim for benefit, although having no children was negatively associated with wave two benefit receipt in Models (1) – (4).
- Area benefit stocks and flows: some of these were significant in estimating time on benefit but they were never significant in estimating wave two benefit status.
- Pre-ONE job: higher pay in this job was associated with reduced time on benefits after ONE, especially where earnings were in the highest bracket, but they were not significantly associated with wave two benefit status. Being a partly – skilled manual worker in the pre-ONE job increased time spent claiming relative to professionals, an effect that was not apparent for wave two benefit receipt.
- General health: mothers with poor or fair health spent more time claiming than those with good health, whereas only those with poor health were more likely to claim out-of-work benefit twelve months after their claim for benefit.
- ONE: being in a PVS control area increases the time on benefit relative to being in a PVS ONE pilot, but ONE does not affect wave two benefit status.

Table 4.16 indicates the significance of variables, and the direction of effects, across all three outcomes for lone mothers, summarising the models in Appendix B. Although the similarities are notable, there are clear differences that need to be borne in mind in constructing profiling models.

Table 4.17 shows the accuracy of profiling based on the OLS for a treatment targeted at a minority, half and nearly three-quarters of the lone mother sample. Correct prediction rates (column 1) for the 30 per cent and 50 per cent cut-off are similar to those for the wave two benefit status models reported in Table 4.12. However, the correct prediction rate is much higher at the 70 per cent cut-off, that is, for carefully targeted treatment on offer to only 30 per cent of the population. For the parsimonious model, the correct prediction rate is 14 percentage points higher when estimating percentage of time on benefit than it is for the model estimating benefit status twelve months after their claim for benefit. The difference is 10 percentage points for the full model. These gains are made through a substantial reduction in the wrong denial rate, which falls by around 20 percentage points, offset by a rise of roughly 10 percentage points in the wrong treatment rate. Thus, as in the case of the sick and disabled, the time on benefit models reduce the number of false negatives but increase the number of false positives.

There is one important respect in which these results differ from those for the sick and disabled: in contrast to the sick and disabled, there are no real gains to be made in using the full model relative to the parsimonious model when profiling for a treatment aimed at 50 per cent or 70 per cent of the sample.

Table 4.16 Guide to significance of variables in lone mother models

	Without a job at wave 2	On OOW benefit at wave 2	Percentage time claiming, ONE-31/12/02
Age (ref: <20 yrs)	ns	- if 20-24 yrs	- if 20-34 yrs
Qualifications (ref: none)	-	-	-
Numeracy problems	ns	ns	+
Housing tenure (ref: owner occupation)	+ if renting	+ if renting or if 'other' tenure	+ if renting
Marital status (ref: single)	- married, separated	- married or cohabiting; + widow	- married, cohabiting; + widow
Number of children (ref: one)	ns	- no children	ns
Age of youngest child (ref: < 3 yrs)	- until 16-18 yrs	- until 16-18 yrs	- until 16-18 yrs
Benefit history in 2 yrs pre-ONE	+ if OOW benefit	ns	ns
% time working 16+ hrs in 2 yrs pre-ONE	- if >66%	- if > 66%	- if >66%
% time working <16 hrs in 2 yrs pre-ONE	- if >50%	ns	ns
Net wage in pre-ONE job	ns	ns	- (u-shaped)
Social class in pre-ONE job (ref: professional, intermediate)	ns	ns	+ if partly skilled manual worker
If ever had job	-	-	-
Any sickness in 2 yrs pre-ONE	ns	+	+
Any education in 2 yrs pre-ONE	ns	-	-
TTWA benefit stocks and flows	ns	ns	- with higher % disabled claimants; + with increasing % disabled
General health (ref: good)	ns	+ if poor	+ if fair or poor
Long-standing illness (ref: none)	+ if says affects work	+ if says affects work	+ if says affects work
Care responsibilities (ref: none)	ns	+ if affects work	+ if affects work
Telephone	-	ns	ns
Licence (ref: no licence, no vehicle access)	- if licence and access	- if licence and access	- if licence and access
Number of household workers (ref: none)	- if one household worker	- if one household worker	- if one household worker
Other regular income except benefits/wages (ref: none)	+	-	ns
Attitudes to working (ref: very negative)	-	-	-

Notes: (1) +/- denote positive and negative significant effects at 95 per cent confidence level or above in at least one of the parsimonious, middling or full models. ns denotes non-significance (2) Variables that are never significant are excluded from this table (3) Area dummies and ONE pilot dummies both had significant effects but are not shown in the table (4) Full tables are appended in Appendix B

Table 4.17 Success in targeting treatment at different cut-offs for treatment allocation using predicted percentage of time claiming out-of-work benefits between ONE eligibility and 31 December 2002

	Correctly predicted	Correctly treated	Wrongly treated	Wrongly denied
30% cut				
M(2)	70	55	15	15
M(6)	70	55	15	15
50% cut				
M(2)	67	33	17	17
M(6)	68	34	16	16
70% cut				
M(2)	68	17	13	19
M(6)	66	16	14	20

Note: treatment allocation in validation sample. 30 per cent cut = time on OOW benefit prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = time on OOW benefit prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = time on OOW benefit prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on OLS model.

Table 4.18 presents the information in Table 4.17 in a different way. Row 1 shows the wrong prediction rate rises slightly with more targeted treatment, whereas there is a steep rise in the case of the wave two benefit status models (see Table 4.13), a difference which was also apparent for the sick and disabled. Again reflecting findings for the sick and disabled, as we move to a more targeted treatment, the wrong prediction rate among those predicted not to need treatment declines (row 2) whereas it rises among those predicted to need treatment (row 3). Row 4 uses as its base the clients whose actual time on benefits is below the rate entitling them to treatment. In 50 per cent of these cases, their predicted time on benefit is higher than the 30 per cent cut-off, resulting in unnecessary treatment. This figure falls progressively with more targeted treatment, as in the case of the sick and disabled. Row 5 uses as its base the clients whose actual time on benefits is above the rate entitling them to treatment. With a 30 per cent cut-off, four-fifths of these clients are actually treated, but this falls to 44 per cent with a 70 per cent cut-off.

Table 4.18 Prediction rates at different cut-offs for treatment allocation using predicted percentage of time on out-of-work benefits, ONE eligibility – 31 December 2002

	30% cut	50% cut	70% cut
Percentage all predictions wrong	30	32	34
Percentage all negative predictions wrong	50	32	29
Percentage all positive predictions wrong	21	32	47
Percentage those with time on benefits below cut-off who are wrongly treated	50	32	22

Percentage those with time on benefits above cut-off who are correctly treated	79	68	44

Notes: prediction rates in validation sample based on M(6) results presented in Table 4.17

We can draw the following inferences from the analysis presented above:

- Profiling outperforms random allocation of the treatment because the models are good at ranking individuals according to the percentage of time they spend claiming out-of-work benefits.
- Whereas average differences in predicted outcomes indicate the 'full' model outperforms the other models, there are no gains to more extensive models using the correct prediction criteria, whichever of our three cut-off points is used to target treatment.
- The OLS estimator marginally outperforms the tobit estimator.
- Influences on early and later benefit outcomes differ, and this needs to be borne in mind in constructing profiling models.
- There are no unambiguous advantages to using percentage of time spent claiming rather than wave two benefit status as the profiling variable: the relative performance of profiling on these two outcomes using identical models differs with the cut-off point chosen to allocate treatment. With a 70 per cent cut-off the correct prediction rate is higher when using percentage of time spent claiming, but profiling based on wave two benefit status results in slightly better profiling with 30 per cent and 50 per cent cut-offs.
- With the exception of point 2, these findings reflect the conclusions drawn from the analysis of the sick and disabled.

5 Analysis and results for JSA clients

- In contrast to the other two client groups, only 42.5 per cent of JSA clients were out of work 12 months after making their initial approach to DWP, and 32 per cent were claiming out-of-work benefits at that point. Furthermore, only two per cent had spent all of their time claiming out-of-work benefits over the 30 month period, the mean percentage of time spent claiming being 30 per cent.
- Profiling outperforms random allocation of the treatment.
- The 'full' model outperforms other models in predicting benefit and labour market status 12 months after claiming but, when profiling with the percentage of time claiming over the 30 month period, there are no improvements in correct prediction rates with the fullest models.
- The predictive power of profiling models for out-of-work benefit and labour market status at the 12 month point are similar, though the determinants of these two statuses differ in a number of respects.
- There are no unambiguous advantages to using percentage of time spent claiming rather than benefit status at month 12 as the profiling variable: the relative performance of profiling on these two outcomes using identical models differs with the cut-off point chosen to allocate treatment.
- Once again, the logit marginally outperforms other estimators in profiling status 12 months on, while the OLS performs better than the tobit estimator in predicting percentage of time claiming over the 30 month period.
- Profiling JSA clients with models devised for the sick and disabled produces poorer results than profiling JSA clients with models devised specifically for them.
- In contrast to the sick and disabled, correct prediction rates rise as the target group for treatment narrows. Again, in contrast to the sick and disabled, the correct prediction rate is not particularly sensitive to the cut-off point chosen.
- Irrespective of the cut-off point, negative predictions are less likely to be wrong in the case of JSA clients compared with the sick and disabled, but a higher percentage of those predicted to need treatment actually find a job.

- Irrespective of the cut-off point, out-of-work correct treatment rates are higher for JSA clients than they are for the sick and disabled.
- Sensitivity analyses made little difference to the results, except in the case of the split by gender and age. How well a profiling instrument performs for any of the four sub-groups (men, women, those aged under 35 years and those aged 35 or more) depends on the criterion used to measure accuracy and the model specification.

Finally we turn to analysis and results for JSA clients in the ONE database. For the purposes of the ONE evaluation, a client is classified as a JSA client if they initially approached the Department about claiming Jobseeker's Allowance (JSA) – whether or not they went on to claim that benefit, and regardless of their benefit status by the time of the first survey interview. 4,933 were interviewed at the first interview and 3,189 were interviewed at the second interview.

5.1 Outcomes for JSA clients

Table 5.1 shows the labour market status of JSA clients twelve months after their claim for benefit: 57.5 per cent were doing some paid work at that point – around double the rate for the sick and disabled and lone parents. The unemployed make up a further 25.5 per cent, and those on Government schemes another 2.7 per cent. Thus, this client group differs markedly from both the sick and disabled and lone parents in that over four-fifths were economically active by the time of the wave two interview. This may, in part, reflect the intervention regime in place for JSA clients that includes a number of mandatory job search components, plus mandatory involvement in the New Deals for longer-term claimants.

Table 5.1 Labour market status twelve months after their claim for benefit

	Weighted column percentage
30+ hours paid work	45.3
16-29 hours paid work	8.9
<16 hours paid work	3.3
Full-time education	3.9
Government scheme	2.7
Unemployed	25.5
Looking after home	3.3
Temporarily sick or injured	3.9
Permanently sick or disabled	1.3
Not working, other reasons	2.0

Base unweighted N=3,189.

Table 5.2 Out-of-work benefits received twelve months after their claim for benefit

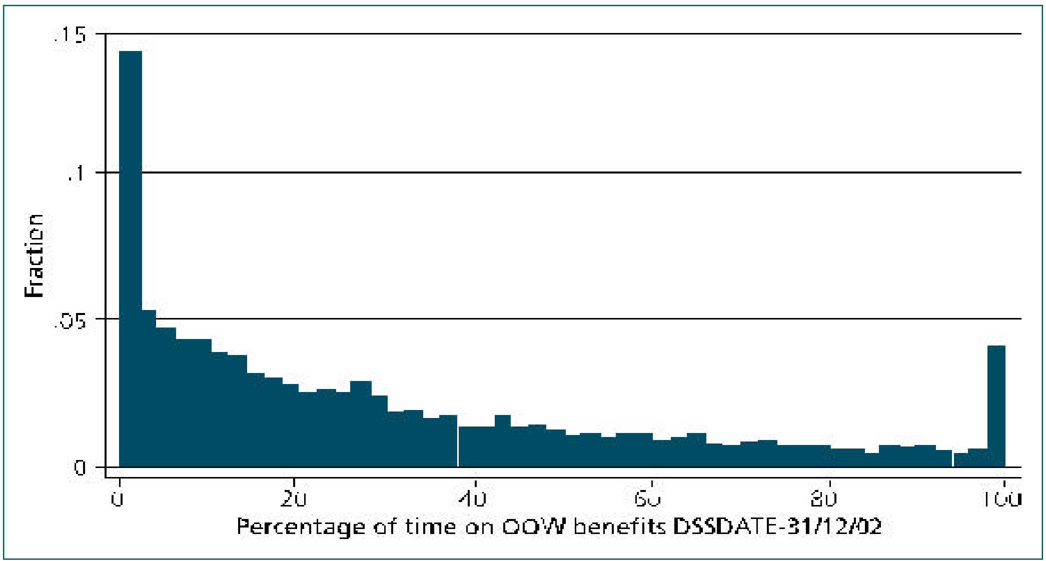
	Weighted cell percentage
Income Support	6.2
Jobseeker's Allowance	23.3
Widow's Benefit	0.2
Incapacity Benefit	2.8
Invalid Care Allowance	0.7
Severe Disablement Allowance	0.2
Any of the above	31.8

Note: unweighted N=3,188. There was 1 case where benefit status could not be accurately determined.

Reflecting this labour market status, the percentage of JSA clients in receipt of out-of-work benefits twelve months after their claim for benefit was around half that for the other two client groups at 32 per cent (Table 5.2). Of those claiming a benefit, around three-quarters were in receipt of JSA and a fifth were in receipt of Income Support. There were 39 JSA clients receiving out-of-work benefits who also said they were working at least 16 hours per week. Only 1.9 per cent were in receipt of more than one out-of-work benefit.

Comparison of Tables 5.1 and 5.2 reveals the percentage in receipt of out-of-work benefits is substantially lower than the percentage without paid work. In fact, 406 JSA clients who had no paid employment did not receive any out-of-work benefits. Of these 406, 357 had partners who were in paid work.

Figure 5.1 Percentage of time spent on out-of-work benefits between ONE eligibility and 31 December 2002, JSA clients



We were able to match 90.4 per cent (4,458 out of 4,933) of the JSA clients who responded at wave one to administrative benefit records. Few (96 cases, or 2.2 per cent) spent all of their time on one or more of the out-of-work benefits qualifying clients for ONE (JSA, IS, IB, ICA, SDA, WB or BB). Furthermore, a substantial percentage of JSA clients (431, or 9.7 per cent) had spent no time at all claiming out-of-work benefits over the period (Figure 5.1). These figures contrast starkly with those for the sick and disabled and lone parents where there were many claiming over the whole period and few with no experience of claiming. This is for two reasons. First, JSA clients were sampled predominantly from the Labour Market System (LMS) recording all people approaching the Department to enquire about a claim. The sick and disabled and lone parents were drawn predominantly from the GMS system that contains claimants only. Clearly, many JSA clients did not go on to register a claim. Secondly, even where JSA clients registered a claim after their ONE entry date, they tended to flow off benefit more quickly than the sick and disabled and lone parents.

5.2 Models used in profiling JSA clients

Figure 5.2 Variables used in models profiling JSA clients

Models (1)-(2)	Models (3)-(4) – as (1) and (2) plus:	Models (5) and (6) – as (3) and (4) plus:
Demographics Gender 9 JSA claimants age dummies Ethnicity - White 7 education dummies If numeracy problems If literacy problems 6 housing tenure dummies 5 dummies for age of youngest child 6 actual marital status dummies Benefit history in two years pre-ONE If ever received out-of-work benefits only If received in-work benefits only If received both out-of-work and in-work benefits If received no benefits Work history in two years pre-ONE 6 dummies for % time working 16+ hours per week 3 dummies for % time working 1-15 hours per week If ever worked before If spent any time in two years before claim in the unemployed state 6 net pay in pre-ONE job dummies 6 social class in last pre-ONE job dummies **Area** 6 dummies for ONE/control areas, OR 24 benefit area dummies	**Demographics** 5 dummies identifying any time in two years before claim spent in the following states: - temporarily sick - permanently sick/ disabled - full-time education - training - other (eg. looking after home)	**Demographics** 3 dummies for general health in last year 3 dummies for long-standing illness Mental disability dummy 3 care responsibility dummies If possess telephone 3 dummies for driving licence and vehicle access 3 dummies for number of household workers 5 dummies for work attitudes 3 dummies for regular income other than earnings/benefits **Area** TTWA benefit stocks/flows for unemployment, lone parents, sick and disabled

The models used for the JSA client analysis are in Figure 5.2: it shows the variables used in the parsimonious (column 1), middling (column 2) and full models (column 3). The breaks used to define dummy variables on covariates such as age and wage differ from those used in the sick and disabled models, reflecting differences in the distribution of the client groups on these variables. Differences in the sets of variables entering the parsimonious, middling and full models reflect differences in the performance of alternative profiling models. As in the case of lone mothers, we also ran analyses using specifications developed for the sick and disabled (presented in Figure 3.2) to allow comparison of results across the two client groups.

Analyses for the three outcomes described in Section 5.1 are presented in turn below. The sensitivity analyses undertaken are identical to those undertaken for the sick and disabled except, as in the case of the lone mothers, we use 35 years as the age cut-off rather than 45 years used for the sick and disabled, reflecting JSA clients' younger age profile.

5.3 Results

5.3.1 Without a job twelve months after their claim for benefit

Table 5.3 shows the mean proportion of JSA clients who were without paid work at the wave two survey interview in each quintile of the predicted distribution of out-of-work probabilities. It does so for the logit, probit and OLS specifications of Models (2) and (6). In the raw data 42.5 per cent of the sample were out of work at that stage, roughly one year after ONE eligibility. If ranked according to actual outcomes, the proportions in Q5 – Q4 would be 1, the proportion in Q3 would be .13, and the proportions in Q2 and Q1 would be zero. Ranking claimants according to their predicted probability of being out of work twelve months after their claim for benefit, depending on the model, 66 – 70 per cent of the highest quintile actually go on to be out of work, compared with 19 – 22 per cent of those in the lowest quintile of predicted probabilities. Differences in the mean proportions out of work by predicted quintile confirm profiling with any of these models is preferable to random allocation where figures vary around .43. The full models differentiate a little better than the parsimonious models, as indicated by the gap between the means in the bottom and top quintiles. The different functional forms perform almost identically.

Table 5.3 Comparison of proportions out of work twelve months after their claim for benefit for JSA clients, by quintiles of predicted out-of-work status for logit, probit and OLS

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Q5	0.67	0.69	0.66	0.70	0.67	0.69
Q4	0.52	0.54	0.52	0.53	0.52	0.54
Q3	0.39	0.42	0.40	0.43	0.38	0.41
Q2	0.30	0.25	0.28	0.25	0.29	0.27
Q1	0.22	0.19	0.23	0.19	0.22	0.19

Note: all models run on 70 per cent sample and results based on 30 per cent validation sample

Table 5.4 compares the predictive performance of the logit, probit and OLS estimators using Models (2), (4) and (6). It presents differences in the proportion predicted out of work between the top and the bottom of the distribution of predicted probabilities.

Table 5.4 Differences in proportion predicted out of work, by quintiles of the predicted probability distribution for JSA clients

	Logit			Probit			OLS		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	0.31	0.32	0.36	0.32	0.32	0.36	0.33	0.33	0.38
T60%-B40%	0.33	0.33	0.38	0.33	0.33	0.38	0.33	0.33	0.38
T40%-B60%	0.36	0.36	0.41	0.35	0.35	0.41	0.34	0.34	0.39
T20%-B80%	0.38	0.39	0.46	0.38	0.38	0.45	0.37	0.37	0.44
Average dif.	0.35	0.35	0.40	0.35	0.35	0.40	0.34	0.34	0.40

Note: models with 24 area dummies; T=top, B=bottom; estimation sample=2232; validation sample = 957

The logit and probit perform equally well across all three models, while the OLS performs slightly worse with the parsimonious and middling models, but identically in the case of the full model. Comparing the average differences in predicted outcomes across Models (2), (4) and (6), there is no gain moving from (2) to (4), but there are clear gains in profiling with Model (6), as indicated by an increase in average differences of five percentage points over the other models. This was true for the sick and disabled too.

Table 5.5 Comparison of average differences in predicted out-of-work probabilities

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Av. dif. for preferred JSA models	.35	.40	.35	.40	.34	.40
Av. dif. for JSA clients with sick and disabled model specification	.32	.39	.32	.39	.31	.39
Av. dif. for sick and disabled	.38	.45	.37	.45	.36	.43

Using the average difference criterion, Table 5.5 compares the performance of the parsimonious and full models for JSA clients and the sick and disabled. The first row is taken from the last row of Table 5.4. The average differences in row one are larger than those in row two where we use the profiling models designed for the sick and disabled. This shows there are gains in profiling JSA clients using a profiling tool dedicated to the client group, rather than a profiling tool designed for the sick and disabled, although the differences for the full model are small.

Table C.2 presents Models (1)–(6) using the logit estimator to illustrate which variables in the models are statistically significant (Table C.1 gives the meaning of variable labels used in the JSA models). In the most parsimonious models (1) and (2), probabilities of being out-of-work twelve months after their claim for benefit fall with qualifications – especially having a degree – being a woman, being white, being married, time spent in paid work (full-time and part-time) in the two years before ONE, and mid-level earnings in the pre-ONE job. They rise where the client rents from the local authority and among those with time spent claiming out of work benefits in the two years before ONE. The non-linear effects of the client's age and age of youngest child are difficult to interpret (perhaps because the two interact), as is the negative effect of having no job in the two years pre-ONE relative to being a professional in one's last job. Results change little with the addition of the variables in Models (3) and (4), except the effects of qualifications and being a woman strengthen, and time spent unemployed in the two years prior to ONE increases out-of-work probabilities. The new work history variables added are not significant. A number of the variables added in the full models ((5) and (6)) replicate effects common in analyses of labour market behaviour of the unemployed, with probabilities of being out of work falling where the client has a telephone, access to a vehicle and a licence to use it, other household workers, positive work attitudes, no care responsibilities and good general health. Regular income (other than benefits or wages) increases out of work probabilities, perhaps by blunting the incentive to work. A more surprising finding is the lower probability of being out of work twelve months after their claim for benefit among those with a long-standing illness that does not affect their work, relative to those without a long-standing illness. Area-level benefit stocks and flows have no significant effect.

Table 5.6 Success in targeting treatment at different cut-offs for treatment allocation using out-of-work probabilities twelve months after their claim for benefit

	Correctly predicted	Correctly treated	Wrongly denied	Wrongly treated
30% cut				
M(2)	58	36	36	7
M(6)	61	37	34	5
50% cut				
M(2)	63	29	23	14
M(6)	65	30	22	13
70% cut				
M(2)	65	20	12	23
M(6)	67	21	11	22

Note: treatment allocation in validation sample. 30 per cent cut = OOW prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = OOW prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = OOW prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on logit model.

Table 5.6 takes the logit Models (2) and (6) discussed above and identifies the percentages in the validation sample who are correctly predicted (column 1), those who are correctly treated (column 2), those who are wrongly treated (column 3), and those who are wrongly denied access to treatment (column 4) at three different cut-off points for treatment. In contrast to the sick and disabled (Table 6), the correct prediction rate rises as the target group for the treatment narrows, with the correct prediction rate highest with a 70 per cent cut-off. Furthermore, and again, in contrast to the sick and disabled, the correct prediction rate is not particularly sensitive to the cut-off point chosen. Thus, whereas the correct prediction rate for the sick and disabled using Model (6) improves by 13 percentage points as one moves from a 70 per cent cut-off to a 30 per cent cut-off, the improvement among JSA clients from a move in the other direction is only six percentage points. Comparing absolute correct prediction rates for JSA clients and the sick and disabled, the sick and disabled models outperform those for the JSA clients at the 30 per cent and 50 per cent cut-offs, but profiling is more accurate for JSA clients than sick and disabled clients at the 70 per cent cut-off. The reason for these differences is apparent when one compares the distribution of the probabilities of being out of work at wave two for the sick and disabled and JSA validation samples (Figures 5.3 and 5.4). Figure 5.3 relates to the JSA client group, and shows the validation sample is fairly evenly spread across the probability distribution, although there is some concentration towards the lower end of the probability distribution. By contrast, the sick and disabled validation sample is heavily concentrated in the top end of the probability distribution, with substantial bunching above the 90th percentile. The distribution for the sick and disabled makes it more difficult to predict accurately with a 70 per cent cut-off. These differences between the performance of the JSA client and sick and disabled models are driven by differences in the underlying distribution of the outcome variable for the two client groups, and the models' ability to identify correctly where clients within a particular client group should be ranked according to their predicted probabilities.

A comparison of Tables 3.5 and 5.6 also reveals a lower wrong denial rate among JSA clients compared with the sick and disabled, but a higher wrong treatment rate and lower correct treatment rate, whatever the cut-off level.

The same information is presented in a different fashion in Table 5.7. Confirming the findings discussed above, and in contrast to the sick and disabled (see Table 3.6), the first row shows the wrong prediction rate falls as the treatment becomes more targeted. At the 30 per cent cut-off, the percentage of all predictions that are wrong is 13 percentage points higher for JSA clients than the sick and disabled but, at the 70 per cent cut-off, the percentage of all predictions that are wrong is nine percentage points higher for the sick and disabled than JSA clients. Negative predictions are less likely to be wrong in the case of the JSA, irrespective of the cut-off point (row 2), but a much higher percentage of those predicted to need treatment actually find a job (row 3), reflecting the much higher labour market activity rates among those out of work among JSA clients relative to sick and disabled clients.

Figure 5.3 Distribution of JSA validation sample's predicted probabilities of being out of work twelve months after their claim for benefit using logit Model (6)

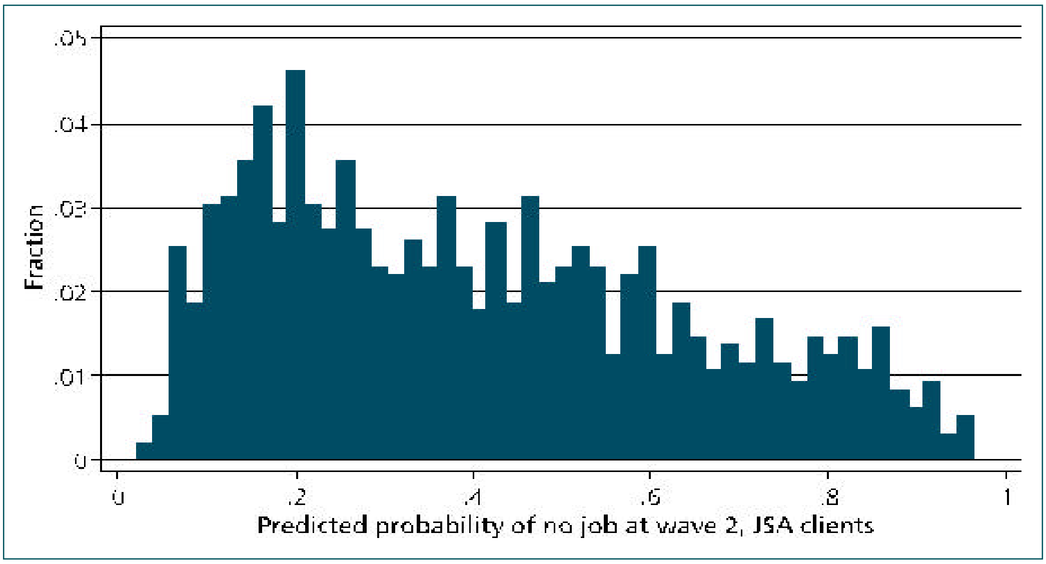


Figure 5.4 Distribution of sick and disabled validation sample's predicted probabilities of being out-of-work twelve months after their claim for benefit using logit Model (6)

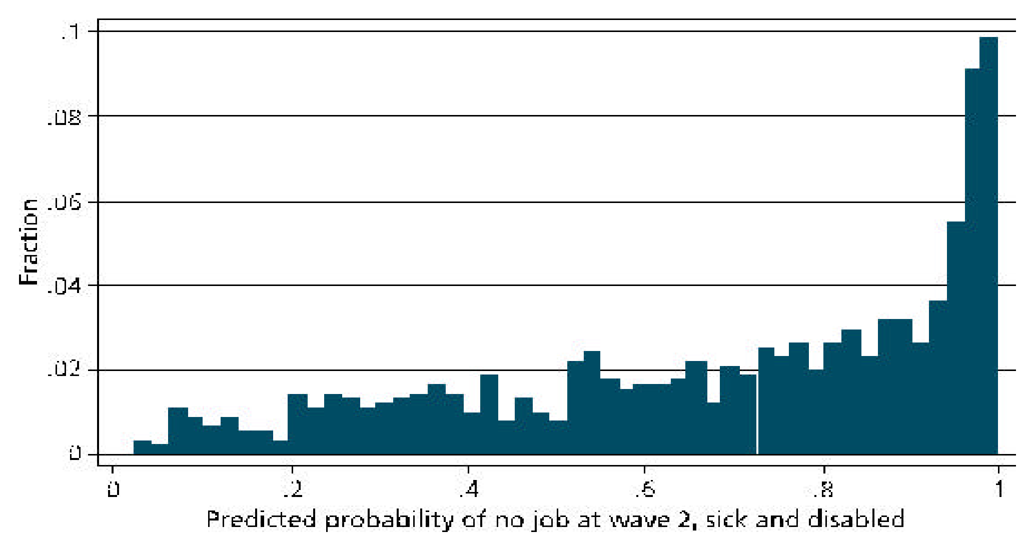


Table 5.7 Prediction rates at different cut-offs for treatment allocation using out-of-work probabilities twelve months after their claim for benefit

	30% cut	50% cut	70% cut
Percentage all predictions wrong	39	35	33
Percentage all negative predictions wrong	17	27	32
Percentage all positive predictions wrong	48	42	34
Percentage in work wrongly treated	60	39	19
Percentage out-of-work correctly treated	86	70	49

Notes: prediction rates in validation sample based on M(6) results presented in Table 5.6

Using actual out-of-work status twelve months after their claim for benefit as its base, row 4 shows 60 per cent of those in work twelve months after their claim for benefit would have been wrongly treated as a result of their profiling prediction where 70 per cent of the sample is treated. This falls to 19 per cent where only 30 per cent of the sample are treated. Finally, row 5 shows 86 per cent of those who actually went on to be out of work twelve months after their claim for benefit would have been treated following profiling with a treatment aimed at 70 per cent of the sample. This falls to 49 per cent in a smaller programme where only 30 per cent are treated. This final set of figures show an accuracy rate that is better than that for the sick and disabled.

Having presented our basic results for this outcome we turn to our sensitivity tests. Results were as follows:

- The inclusion of ward-level deprivation data made no difference to results.
- Re-estimating models excluding benefit area variables resulted in a one percentage point fall in average differences in the logit parsimonious model, and no difference in the full model. Correct prediction rates are virtually identical with and without area variables.
- Switching to an 80:20 split between the estimation and validation samples makes very little difference to differences in out-of-work predictions across quintiles of the predicted probabilities and the percentage of correct predictions.

- Confining the sample to those respondents who said at the wave one interview that they had made a claim for benefits (dropping 334 non-claimants) resulted in a one percentage point improvement in average differences in the parsimonious and full models. Correct prediction rates with a 30 per cent cut-off improved by two percentage points in the case of the parsimonious model and by one percentage point with the full model. Correct prediction rates were one to two percentage points lower for the claimant-only sample than the whole sample at the 70 per cent cut-off. Overall, then, confining the JSA sample to those who said they had claimed by wave one makes little difference to the performance of the profiling models.
- Running separate profiling models by gender, average differences indicate a better performance for models profiling women (Table 5.8). However, correct prediction rates present a more complicated picture of profiling accuracy by gender. With a 30 per cent cut-off, correct prediction rates are roughly 10 percentage points lower for women than men but, with a 70 per cent cut-off, correct prediction rates for women are similar to men with the full model and better with the parsimonious model.
- Running separate profiling models by age, average differences were better for the older age group (35+) for both the parsimonious and full models (Table 5.9). However, although correct prediction rates are superior for the 35+ age group at the 70 per cent cut-off, correct prediction rates are lower for the older age group with the parsimonious model and a 30 per cent cut-off. Correct prediction rates are identical for the two age groups with a full model at the 70 per cent cut-off.

Table 5.8 Diagnostics for out-of-work status twelve months after their claim for benefit, by gender for JSA clients

	Men		Women	
	M(1)	M(5)	M(1)	M(5)
Average difference	.38	.39	.41	.47
Percentage correct predictions (30% cut-off)	61	63	50	52
Percentage correct predictions (70% cut-off)	63	67	68	66

Logits, with 70% estimation sample, 30% validation sample. Sample sizes: men, N=2130; women, N=1059

Table 5.9 Diagnostics for out-of-work status twelve months after their claim for benefit, by age for JSA clients

	<35 years		35+ years	
	M(1)	M(5)	M(1)	M(5)
Average difference	.36	.42	.38	.47
Percentage correct predictions (30% cut-off)	58	59	55	59
Percentage correct predictions (70% cut-off)	62	66	68	72

Logits, with 70% estimation sample, 30% validation sample: Sample sizes: those under 35, N=1687; those aged 35 and more, N=1502

The inferences we draw from the analysis of wave two out-of-work status for JSA clients are as follows:

- Profiling outperforms random allocation of the treatment.
- The 'full' model outperforms the other models.
- There is little to choose between functional forms but the logit and probit estimators perform better than the OLS estimator.
- Profiling JSA clients with models devised for the sick and disabled produces poorer results than profiling JSA clients with models devised specifically for them.
- Profiling models for the sick and disabled perform better than the JSA models using the average difference criterion.
- In contrast to the sick and disabled, correct prediction rates rise as the target group for treatment narrows. Again, in contrast to the sick and disabled, the correct prediction rate is not particularly sensitive to the cut-off point chosen.
- Irrespective of the cut-off point, negative predictions are less likely to be wrong in the case of JSA clients compared with the sick and disabled, but a higher percentage of those predicted to need treatment actually find a job.
- Irrespective of the cut-off point, out-of-work correct treatment rates are higher for JSA clients than they are for the sick and disabled.
- Sensitivity analyses made little difference to the results, except in the case of the split by gender and age. How well a profiling instrument performs for any of the four sub-groups (men, women, those aged under 35 years and those aged 35 or more) depends on the criterion used to measure accuracy and the model specification.

5.3.2 Claiming out-of-work benefit twelve months after their claim for benefit

Identical analyses were undertaken to predict the probability of claiming one or more out-of-work benefits at the second wave interview. As shown in Table 5.2, around three-in-ten of wave two respondents said they were in receipt of these out-of-work benefits. In fact, 39 JSA clients said they were in receipt of out-of-work benefits and in paid work of 16 hours or more, so we tested the sensitivity of results to the exclusion of this group.

Table 5.10 Comparison of proportions claiming out-of-work benefits twelve months after their claim for benefit for JSA clients, by quintiles of predicted out-of-work benefit status for logit, probit and OLS

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Q5	0.55	0.63	0.56	0.63	0.56	0.64
Q4	0.37	0.35	0.37	0.35	0.35	0.36
Q3	0.26	0.28	0.27	0.27	0.28	0.26
Q2	0.18	0.15	0.19	0.15	0.19	0.16
Q1	0.12	0.07	0.11	0.07	0.11	0.06

Note: all models run on 70 per cent sample and results based on 30 per cent validation sample

If ranked by quintile according to their actual wave two status, the proportions of JSA clients in Q5 would be 1.0, the proportion in Q4 would be .6, and the proportion in Q3-Q1 would be zero. Table

5.10 compares the proportion of JSA clients claiming out-of-work benefits twelve months after their claim for benefit, ranked according to their predicted probability of benefit receipt using logit, probit and OLS Models (2) and (6). Depending on the model, 55-64 per cent of the highest quintile actually go on to claim out-of-work benefit, compared with 6-12 per cent of those in the lowest quintile of predicted probabilities. All models perform better than random allocation, where the proportion claiming in each quintile would fluctuate around .32. The full models do a better job at ranking individuals according to their future benefit status. There is little to choose between the performance of the different functional forms.

Table 5.11 compares the predictive performance of the logit, probit and OLS using Models (2), (4) and (6). Comparing across functional forms, the average differences in predicted outcomes are very small. In each case, the most parsimonious model, M(2), performs reasonably well; there are no gains moving from M(2) to M(4), but the fullest model performs best. These average differences are similar to those for the equivalent out-of-work labour market status models reported in Table 5.4.

Table 5.11 Differences in proportion predicted to receive out-of-work benefits, by quintiles of the predicted probability distribution, JSA clients

	Logit			Probit			OLS		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	0.30	0.31	0.33	0.31	0.31	0.33	0.35	0.35	0.39
T60%-B40%	0.34	0.34	0.37	0.34	0.34	0.37	0.34	0.34	0.38
T40%-B60%	0.37	0.38	0.43	0.37	0.37	0.42	0.34	0.35	0.40
T20%-B80%	0.43	0.44	0.50	0.42	0.43	0.48	0.39	0.39	0.44
Average dif.	0.36	0.36	0.41	0.36	0.36	0.40	0.35	0.36	0.40

Note: models with 24 area dummies; T=top, B=bottom; estimation sample=2232; validation sample = 956

Using the average difference criterion, Table 5.12 compares the performance of the parsimonious and full models for JSA clients and the sick and disabled. The first row is taken from the last row of Table 5.11. Row 2 shows profiling JSA clients with models designed for the sick and disabled reduces performance marginally. Row 3 replicates the average differences from the sick and disabled models presented in Table 3.11. Using parsimonious models, average differences are greater for the JSA clients than they are for the sick and disabled, but average differences are a little larger for the sick and disabled when using the full models.

Table 5.12 Comparison of average differences in predicted out-of-work probabilities

	Logit		Probit		OLS	
	M(2)	M(6)	M(2)	M(6)	M(2)	M(6)
Average differences for preferred JSA client models	.36	.41	.36	.40	.35	.40
Average differences for JSA clients with sick and disabled model specification	.34	.40	.34	.40	.34	.40
Average differences for sick and disabled	.32	.43	.32	.43	.32	.43

Table C.3 presents Models (1) – (6) using the logit estimator to illustrate which variables in the models have a significant impact predicting out-of-work benefit status twelve months after their claim for benefit. Effects differ in a number of ways from those presented in Table C.2 for out-of-work labour market status. Being female, being white, the age of the youngest child, regular income other than benefits and earnings, time spent unemployed in the two years pre-ONE, and experience working part-time in the two years prior to ONE are no longer significant. Other effects are attenuated: for instance, the negative effects of age are confined to being aged 20 – 24 years in Models (1) to (4). Other factors are significant in estimating out-of-work benefit status that were not significant in estimating out-of-work labour market status. These include the positive effects of numeracy problems, renting privately, living in an institution, cohabitation, and the negative effects of illness and education in the two years pre-ONE. So, as was the case with the sick and disabled, JSA clients' determinants of benefit status differ somewhat from the determinants of labour market status.

Table 5.13 shows how good the profiling models are at targeting treatment on those who go on to claim out-of-work benefits twelve months after their claim for benefit. The results are based on logit Models (2) and (6) and are thus comparable to those presented for out-of-work labour market status in Table 5.6. The correct prediction rates (column 1) for benefit receipt are better than those for labour market status at the 70 per cent cut-off, but they are worse than the labour market status predictions at the 30 per cent cut-off. Whatever the cut-off, wrong treatment rates are higher for the benefit status than labour market status (column 3 in both tables) but wrong denial rates are lower (column 4 in both tables).

Table 5.13 Success in targeting treatment at different cut-offs for treatment allocation using out-of-work benefit receipt probabilities twelve months after their claim for benefit

	Correctly predicted	Correctly treated	Wrongly denied	Wrongly treated
30% cut				
M(2)	51	27	4	45
M(6)	54	28	3	44
50% cut				
M(2)	62	23	8	31
M(6)	67	25	6	28
70% cut				
M(2)	69	16	15	16
M(6)	73	18	13	15

Note: treatment allocation in validation sample. 30 per cent cut = OOW benefit receipt prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = OOW benefit receipt prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = OOW benefit receipt prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on logit model.

Correct prediction rates are sensitive to the cut-off point used, as they are for the sick and disabled. However – as in the case of the out-of-work labour market status discussed above – the correct prediction rate rises as the target group for the treatment narrows, with the correct prediction rate highest with a 70 per cent cut-off. This contrasts with the sick and disabled (Table 3.12) where correct prediction rates were highest with the 30 per cent cut-off. Comparing absolute correct prediction rates for JSA clients and the sick and disabled, the sick and disabled models outperform those for the JSA clients at the 30 per cent cut-off, but profiling is more accurate for JSA clients than sick and disabled clients at the 70 per cent cut-off. A comparison of Tables 3.12 and 5.13 also reveals a lower wrong denial rate among JSA clients compared with the sick and disabled, but a higher wrong treatment rate and lower correct treatment rate, whatever the cut-off level. This last finding echoes that for the analysis of labour market out-of-work status.

Table 5.14 Prediction rates at different cut-offs for treatment allocation using out-of-work benefit receipt probabilities twelve months after their claim for benefit

	30% cut	50% cut	70% cut
Percentage all predictions wrong	47	34	28
Percentage all negative predictions wrong	11	13	19
Percentage all positive predictions wrong	61	54	44
Percentage in work wrongly treated	64	41	20
Percentage out of work correctly treated	90	81	58

Notes: prediction rates in validation sample based on M(6) results presented in Table 5.13

Table 5.14 presents the information in Table 5.13 in a slightly different way. Row 1 shows the wrong prediction rate falls as treatment becomes more targeted, the decline being more pronounced than in the case of out-of-work labour market status (Table 5.7). The percentage of negative predictions that are wrong is considerably lower than in the case of out-of-work labour market status (row 2 in Tables 5.14 and 5.7), and only rises a little with more targeted treatment. However, the percentage of positive predictions that are wrong (which falls with more targeted treatment) is higher than in the case of out-of-work labour market status (row 3). The percentage in work who are wrongly treated (row 4) is a little higher than in the case of out-of-work labour market status, whereas the percentage out of work who are correctly treated is higher.

Sensitivity tests revealed the following:

- The exclusion of the 39 clients claiming out-of-work benefits and working 16 or more hours per week made little difference to the predictive accuracy of the models as measured in average differences and correct prediction rates.
- The addition of ward-level deprivation indices has no effect on the predictive accuracy of the models.
- Models run on claimants only (that is, those saying they were in receipt of one or more out-of-work benefits at wave one) performed a little better than the full sample models, raising average differences by one percentage point with the parsimonious model and three percentage points with the full model. Correct prediction rates also rose by one to two percentage points, except for the full model at the 30 per cent cut-off where correct prediction rates were identical.
- Running the analysis on a random 80 per cent of the sample and validating it on a 20 per cent random sample had little effect on the profiling diagnostics.
- Splitting the sample by age, profiling performs better for JSA clients aged 35+ relative to those aged under 35. Average differences are three percentage points higher with the parsimonious model, and six percentage points higher with the full model. With the 30 per cent cut-off, correct prediction rates were two percentage points higher with the parsimonious model and five percentage points higher with the full model. At the 70 per cent cut-off the differentials were six and four percentage points respectively.
- Splitting the sample by gender, average differences are four percentage points higher for samples run on women compared to men. However, although correct prediction rates are a little higher for women at the 70 per cent cut-off, they are lower with a 30 per cent cut-off.

We can infer the following from the analysis presented above:

- The predictive power of profiling models for out-of-work benefit status twelve months after their claim for benefit was similar to that for out-of-work labour market status twelve months after their claim for benefit: average differences were similar and, whereas correct prediction rates were better for the out-of-work labour market status with a 30 per cent cut-off, they were better for out-of-work benefit status at the 70 per cent cut-off.
- Determinants of benefit and out-of-work status differed in a number of respects, and the JSA models predict better for the JSA clients than the sick and disabled models, confirming the need to develop dedicated profiling tools for different client groups and across outcomes.
- Results were broadly similar when performing sensitivity tests, although there were differences in performance when separate models were run by age and gender.

5.3.3 Time claiming out-of-work benefits after ONE

This section analyses the percentage of time JSA clients spent on out-of-work benefits between ONE eligibility and 31 December 2002. All JSA clients became eligible for ONE between 27 May and 30 June 2000, so the percentage is calculated over a period of around two and a half years.

Table 5.15 Percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002, by quintiles of predicted time claiming benefits OLS and tobit

		OLS			Tobit		
Distribution in the data		**M(2)**	**M(4)**	**M(6)**	**M(2)**	**M(4)**	**M(6)**
Q5	.79	.42	.43	.43	.42	.43	.43
Q4	.40	.39	.37	.36	.38	.37	.36
Q3	.21	.31	.32	.32	.32	.33	.32
Q2	.09	.25	.23	.25	.24	.22	.25
Q1	.01	.19	.20	.21	.20	.21	.21

Note: all models run on 70 per cent sample (N=3,121) and results based on 30 per cent validation sample (N=1,337)

There is bunching at the bottom end of this continuous variable, with 431 of the 4,458 JSA clients successfully matched to the benefit data spending none of their time since ONE eligibility on out-of-work benefits. We test the sensitivity of our profiling on this outcome to the OLS and tobit functions, the latter taking account of the bunching of observations at the lower bound of the dependent variable.

Table 5.15 shows the percentage of time JSA clients spent claiming out-of-work benefits between ONE eligibility and 31 December 2002. The overall mean time spent on out-of-work benefits in the data is 30 per cent. If ranked according to the actual time spent claiming in the raw data, those in the top quintile spent around four-fifths of their time claiming out-of-work benefits (column 1). This falls by a half to 40 per cent in Q4, halves again to 21 per cent in Q3, and again to nine per cent in Q2. Those in the lowest quintile spend virtually no time (one per cent) claiming.

Ranking clients according to their predicted percentage of time on out-of-work benefits since ONE eligibility, the mean percentage of time on benefit among the highest quintile is 42 – 43 per cent (depending on the model), compared with 20 – 21 per cent among those in the lowest quintile. This 2:1 ratio between the top and the bottom quintiles is similar to that found for the sick and disabled and lone mothers (Tables 3.14 and 4.14 respectively). Where clients are randomly assigned to quintiles, the mean percentage of time on benefits fluctuates around 30 per cent, so profiling performs better than random allocation of treatment. There is nothing to choose between the performance of the OLS and tobit estimators in terms of their ability to rank the validation sample by their actual benefit outcome. As in the case of the lone mothers, the full models perform no better than the middling and parsimonious models in ranking JSA clients by their future benefit outcomes.

Table 5.16 compares the predictive performance of the OLS and tobit using Models (2), (4) and (6). It presents differences in the average predicted time on out-of-work benefits between the top and the bottom of the distribution of predicted percentage of time claiming.

Comparing the average differences in predicted outcomes across functional forms, the OLS estimator outperforms the tobit estimator for all three models. The predictive power of the models is not driven by 'success' in any particular part of the distribution. Comparing the average differences in predicted outcomes across OLS Models (2), (4) and (6), the most parsimonious model performs reasonably well, but there are small gains moving from (2) to (6).

Table 5.16 Differences in percentage of time spent claiming out-of-work benefits between ONE eligibility and 31 December 2002, by quintiles of predicted distribution

	OLS			Tobit		
	M(2)	M(4)	M(6)	M(2)	M(4)	M(6)
T80%-B20%	16.2	16.4	17.7	14.2	14.2	15.3
T60%-B40%	15.8	15.9	17.1	14.3	14.3	15.2
T40%-B60%	16.1	16.4	17.3	14.9	15.2	16.0
T20%-B80%	17.3	18.1	19.1	16.4	17.1	18.1
Average difference	16.4	16.7	17.8	14.9	15.2	16.1

Note: all models run on 70 per cent sample (N=3,121) and results based on 30 per cent validation sample (N=1,337); T=top; B=bottom

Table C.4 presents Models (1) – (6) using the OLS estimator to illustrate which variables in the models are statistically significant. The bullet points below compare results with those for identical OLS models (not shown) estimating the probability of being in receipt of out-of-work benefits twelve months after their claim for benefit. The commentary focuses on results that differ from those discussed in the analysis of wave two benefit receipt. It is clear that there are a number of differences between the two models:

- Gender: being a woman had no effect on benefit receipt twelve months after their claim for benefit, but it was associated with a lower percentage of time spent on out-of-work benefits through to December 2002.
- Age: in Models (1) to (4), those aged 20 – 24 had lower probabilities of benefit receipt twelve months after their claim for benefit than JSA clients aged under-20, whereas age was not significant in estimating time spent on out-of-work benefits.
- Qualifications: degree-level qualifications reduced time on benefits in Models (1) and (2), but this was the only qualifications effect. Yet qualifications at A-level or above were associated with lower probabilities of claiming out-of-work benefits twelve months after their claim for benefit across all models.
- Numeracy problems: numeracy problems had no significant effect on time spent claiming, but

they raised the probability of receiving out-of-work benefits twelve months after their claim for benefit in Models (1) to (4).

- Marital status: those who were married or cohabiting at wave one had a lower probability of out-of-work benefit receipt twelve months after their claim for benefit, but their marital status was not significant for time spent claiming out-of-work benefits.
- Housing tenure: renting from the local authority or a housing association was associated with spending more time on out-of-work benefits in all models, whereas housing association renting was not associated with benefit status twelve months after their claim for benefit. Conversely, private renting and living in an institution were both associated with higher probabilities of benefit receipt twelve months after their claim for benefit, whereas private renting only increased percentage of time claiming in Model (4). 'Other' tenure status was associated with a higher percentage of time on benefits, but not with wave two benefit status.
- Benefit claiming in the two years pre-ONE: receipt of both out-of-work and in-work benefits over the pre-ONE period increased the time spent claiming out-of-work benefits but was not associated with benefit status twelve months after their claim for benefit.
- Time in paid work pre-ONE: more time in full-time paid work in the two years pre-ONE reduced the probability of benefit claiming twelve months after their claim for benefit, but it was not associated with the percentage of time claiming through to December 2002.
- Pre-ONE job: lower occupational status was strongly associated with spending more time on out-of-work benefits but, with the exception of having no job pre-ONE, occupational effects were not significantly associated with benefit status twelve months after their claim for benefit.
- Health: illness in the two years pre-ONE lowered the probability of out-of-work benefit receipt twelve months after their claim for benefit but was positively associated with percentage of time claiming out-of-work benefits. The positive association between poor general health and benefit claiming was more strongly associated with time spent claiming. Whereas having a long-standing illness that did not affect work lowered benefit receipt probabilities twelve months after their claim for benefit, it was not significant for time on benefits.
- Telephone: having a telephone lowered the probability of being on out-of-work benefits twelve months after their claim for benefit but it wasn't significant in estimating time on out-of-work benefits.
- Work attitudes: although positive work attitudes lowered benefit probabilities twelve months after their claim for benefit they were not significant in reducing time spent on benefits over the longer term.
- ONE: time spent claiming was lower in the control for Basic ONE than it was in the Basic ONE areas, whereas ONE status did not affect benefit status twelve months after their claim for benefit.

Table 5.17 indicates the significance of variables, and the direction of effects, across all three outcomes for JSA clients, summarising the models in Appendix C. Although the similarities are notable there are clear differences – especially in the effects on wave two benefit status and the percentage of time spent claiming over the two and a half years since ONE eligibility. These need to be borne in mind in constructing profiling models.

Table 5.18 shows the accuracy of profiling based on the OLS profiling tool. Correct prediction rates (column 1) for the 30 per cent cut-off are much better than those for the wave two benefit status models reported in Table 5.13. Correct prediction rates are not particularly sensitive to the cut-off rate. Regardless of the cut-off, correct prediction rates are lower than in the case of the sick and disabled: the difference is particularly marked at the 50 per cent cut-off, but at the 70 per cent cut-off the differential is only one to two percentage points. There are two features of Table 5.18 which are surprising in the light of the analyses presented to date. First, the wrong treatment and wrong denial rates change very little with cut-offs and model specification. Second, the parsimonious models actually outperform the full models by one to two percentage points.

Table 5.19 presents the information in Table 4.17 in a different way. JSA clients' wrong prediction rate fell with more targeted treatment when profiling with benefit status twelve months after their claim for benefit (Table 5.14, row 1). This pattern is not apparent for time spent on out-of-work benefits (row 1). In contrast to the findings for benefit status twelve months after their claim for benefit presented in Table 5.14, the percentage of all negative predictions that are wrong falls with more targeted treatment (row 2) and the percentage of all positive predictions that are wrong rises (row 3). Row 4 uses as its base the clients whose actual time on benefits is below the rate entitling them to treatment. In 59 per cent of these cases, their predicted time on benefit is higher than the 30 per cent cut-off, resulting in unnecessary treatment. This figure falls progressively with more targeted treatment, as in the case of the sick and disabled. Row 5 uses as its base the clients whose actual time on benefits is above the rate entitling them to treatment. With a 30 per cent cut-off, three-quarters of these clients are actually treated, but this falls to 43 per cent with a 70 per cent cut-off.

Table 5.17 Guide to significance of variables in JSA models

	Without a job at wave 2	On OOW benefit at wave 2	Percentage time claiming, ONE-31/12/02
Age (ref: <20 yrs)	- if 20-24 or 40-44	- if 20-24 yrs	ns
Woman	-	ns	-
White	-	ns	ns
Qualifications (ref: none)	-	-	- if degree
Numeracy problems	ns	+	ns
Housing tenure (ref: owner occupation)	+ if renting from local authority	+ if private or local authority renter, or if living in institution	+ if renting or 'other' tenure
Marital status (ref: single)	- married	- married or cohabiting	ns
Age of youngest child (ref: < 3 yrs)	- 3-4 yrs	ns	ns
Benefit history in 2 yrs pre-ONE	+ if OOW benefit	+ if OOW benefit	+ if OOW benefit or both OOW and in-work benefits
% time working 16+ hrs in 2 yrs pre-ONE	- if >66%	- if > 66%	ns
% time working <16 hrs in 2 yrs pre-ONE	- if >50%	ns	ns
Net wage in pre-ONE job (ref: < £110 pw)	- if £150-254	- if £185-254	+ if £150-184
Social class in pre-ONE job (ref: professional, intermediate) skilled, skilled manual	- if no job pre-ONE	- if no job pre-ONE	+ if no job, unskilled, part-
Any unemployment in 2 yrs pre-ONE	+	ns	ns
Any sickness in 2 yrs pre-ONE	ns	ns	ns

Continued

Table 5.17 Continued

	Without a job at wave 2	On OOW benefit at wave 2	Percentage time claiming, ONE-31/12/02
Any illness in 2 yrs pre-ONE	ns	-	+
Any education in 2 yrs pre-ONE	ns	-	+
TTWA benefit stocks and flows	ns	- as unemployment rises	+ as % disability benefits rises
General health (ref: good)	+ if poor	+ if poor	+ if poor or fair
Long-standing illness (ref: none)	- if says LSI does not affect work	- if says LSI does not affect work	ns
Care responsibilities (ref: none)	+ if affects work	+ if affects work	ns
Receives child support payments	ns	ns	-
Telephone	-	-	ns
Licence (ref: no licence, no vehicle access)	- if licence and access	- if licence and access	- if licence and access
Number of household workers (ref: none)	- if 2+ household workers	- if one or more household workers	ns
Other regular income except benefits/wages (ref: none)	+	ns	ns
Attitudes to working (ref: very negative)	-	-	ns

Notes: (1) +/- denote positive and negative significant effects at 95 per cent confidence level or above in at least one of the parsimonious, middling or full models. ns denotes non-significance (2) Variables that are never significant are excluded from this table (3) Area dummies and ONE pilot dummies were generally not significant (4) Full tables are in Appendix C

Table 5.18 Success in targeting treatment at different cut-offs for treatment allocation using predicted percentage of time claiming out-of-work benefits between ONE eligibility and 31 December 2002

	Correctly predicted	Correctly treated	Wrongly denied	Wrongly treated
30% cut				
M(2)	68	55	16	16
M(6)	66	54	17	17
50% cut				
M(2)	63	32	19	19
M(6)	62	32	19	19
70% cut				
M(2)	66	13	17	17
M(6)	65	13	17	17

Note: treatment allocation in validation sample. 30 per cent cut = time on OOW benefit prediction at 30th percentile (so 70 per cent treated); 50 per cent cut = time on OOW benefit prediction at 50th percentile (so 50 per cent treated); 70 per cent cut = time on OOW benefit prediction at 70th percentile (so 30 per cent treated). Wrongly treated means false positive. Wrongly denied means false negative. Predictions based on OLS model.

Table 5.19 Prediction rates at different cut-offs for treatment allocation using predicted percentage of time on out-of-work benefits, ONE eligibility – 31 December 2002

	30% cut	50% cut	70% cut
Percentage all predictions wrong	34	38	35
Percentage all negative predictions wrong	59	39	24
Percentage all positive predictions wrong	24	37	57
Percentage those with time on benefits below cut-off who are wrongly treated	59	39	24
Percentage those with time on benefits above cut-off who are correctly treated	76	63	43

Notes: prediction rates in validation sample based on M(6) results presented in Table 57

We can draw the following inferences from the analysis presented above:

- Profiling outperforms random allocation of the treatment because the models are good at ranking individuals according to the percentage of time they spend claiming out-of-work benefits.
- Whereas average differences in predicted outcomes indicate there are small gains to be made in profiling with the 'full' model, correct prediction rates indicate there are no gains to more extensive models, whichever of our three cut-off points is used to target treatment.
- The OLS estimator marginally outperforms the tobit estimator.
- Influences on early and later benefit outcomes differ.
- There are no unambiguous advantages to using percentage of time spent claiming rather than wave two benefit status as the profiling variable: the relative performance of profiling on these two outcomes using identical models differs with the cut-off point chosen to allocate treatment. With a 30 per cent cut-off the correct prediction rate is higher when using percentage of time spent claiming, but profiling based on wave two benefit status results in better profiling with a 70 per cent cut-off.
- With the exception of point 2, these findings reflect the conclusions drawn from the analysis of the sick and disabled.

6 Conclusions

- Profiling outperforms the random allocation of treatments but wrong denial and wrong treatment rates are not trivial.
- Whether statistical profiling performs accurately enough for policy purposes is a subjective judgement.
- It would be useful to compare the accuracy rates of statistical profiling with those achieved through PA discretion and the application of deterministic rules.
- The accuracy of profiling turns on the distribution of the outcome variable, the proportion of the client group eligible for treatment, and the variables available to predict the outcome.
- Profiling accuracy rates are at least as good, if not better, for the sick and disabled client group as they are for lone mothers and JSA clients.

This study illustrates the performance of profiling in allocating treatment for three DWP client groups: the sick and disabled, lone parents and JSA clients. It does so for three outcomes – being out of work roughly a year after enquiring about a new claim, receiving out-of-work benefits roughly a year later, and percentage of time on out-of-work benefits between ONE eligibility and 31 December 2002, some 30 or so months later. In this concluding chapter we bring together the main results from the study and draw out some practical implications.

6.1 Results

6.1.1 Profiling performs better than random allocation

This is a low hurdle to overcome and the wrong prediction rates are not trivial. Deadweight – individuals identified as needing treatment who, in fact, go on to do well without treatment – is particularly acute where treatment eligibility is wide (column 2 of Table 6.1). The denial of treatment to those who, it turns out, need it, is a greater problem where a smaller percentage of the client group are eligible for treatment (column 3). We do not know how accurate profiling is relative to caseworker discretion or the application of deterministic rules. Nor can we tell from the exercise in this study whether profiling in the field will result in higher or lower accuracy rates than those presented here.

6.1.2 The accuracy of profiling

The accuracy of profiling turns on three factors:

- the distribution of the outcome variable;
- the proportion of the client group eligible for treatment;
- the variables available to predict the outcome variable.

Profiling is accurate when predicted probabilities of the outcome allow clients to be ranked according to their actual subsequent labour market and benefit experiences. Where there is severe bunching in the distribution of an outcome – for example, where only a small proportion of clients move off out-of-work benefits in a given period – this can make profiling difficult because modelling usually performs better where there is reasonable variance in the outcome. However, we find this is not always the case: correct prediction rates are not necessarily higher just because we use the percentage of time claiming rather than benefit status a year after ONE entry. For example, with a 70 per cent cut-off, the correct prediction rate for JSA clients is 73 per cent where the outcome is benefit status and wave two, but only 65 per cent where it is the percentage of time claiming out-of-work benefits (see the last column in Table 6.1).

The proportion of the client group eligible for treatment is also vital because it determines the 'cut-off' point for predicted probabilities above which clients will be prioritised for treatment. The relationship between the distribution of predicted outcomes and the chosen 'cut-off' is a crucial determinant of profiling accuracy. The final column in Table 6.1 shows that, in most cases, correct prediction rates are lower where the eligible group is smaller (that is, where the 70 per cent cut-off is used rather than the 30 per cent cut-off). This is because, as eligibility for treatment is narrowed, the rise in the percentage of clients wrongly denied treatment tends to outweigh the reduction in the percentage of clients wrongly treated. However, this is not always so. In the case of JSA clients, correct prediction rates are higher where eligibility is narrower because the drop in the percentage wrongly treated outweighs the rise in the percentage wrongly denied treatment.

Comparisons of predictive accuracy using parsimonious and fuller models indicate that profiling with a relatively small set of covariates can produce reasonable results. However, this can usually be improved upon with a larger set of covariates. We find that, although a greater number of covariates does not guarantee more accurate profiling – and, in some cases, secures no improvements at all – our 'fuller' models tend to perform better than the most parsimonious models. This is because they contain important information on issues such as work attitudes, caring responsibilities, other household workers and health indicators that prove to be important predictors of outcomes for our three client groups. In our data, some of the variables such as work attitudes are actually collected some time after making an approach to the Department about benefit claiming, so that they may be a function of the claiming process itself. However, it is likely that, if such data were collected at the outset, they would prove to be useful profiling variables.

Although there were many similarities, the influences on our three profiling outcomes differed somewhat, suggesting different outcomes merit different profiling models.

Less important in determining the accuracy of profiling is the functional form of the estimator used. Logit, probit and OLS estimators were tested for predictions of (0,1) outcomes, and OLS and tobit models were estimated for the percentage of time spent claiming. Although there is little to choose between them, the logit estimator performed at least as well as the others for binary outcomes, while to OLS tended to outperform the tobit for continuous outcomes.

Table 6.1 Profiling accuracy across client groups and profiling outcomes

	Percentage wrongly treated	Percentage wrongly denied	Percentage correctly predicted
Sick and disabled:			
OOW W2:			
30% cut-off	14	12	74
70% cut-off	2	39	58
OOW benefit W2:			
30% cut-off	14	10	76
70% cut-off	3	38	59
Percentage time OOW benefit:			
30% cut-off	12	12	76
70% cut-off	10	21	69
Lone mothers:			
OOW W2:			
30% cut-off	12	15	73
70% cut-off	3	46	51
OOW benefit W2:			
30% cut-off	15	11	74
70% cut-off	4	40	56
Percentage time OOW benefit:			
30% cut-off	15	15	70
70% cut-off	14	20	66
JSA clients:			
OOW W2:			
30% cut-off	34	5	61
70% cut-off	11	22	67
OOW benefit W2:			
30% cut-off	44	3	54
70% cut-off	15	13	73
Percentage time OOW benefit:			
30% cut-off	17	17	66
70% cut-off	17	17	65

Notes: (1) Table summarises Model (6) results presented in the main body of the paper (2) OOW W2 means out-of-work labour market status at wave two survey interview; OOW benefit W2 means in receipt of one or more out-of-work benefits at wave two survey interview; percentage time OOW benefit is the percentage of time claiming out-of-work benefits between ONE eligibility and 31 December 2002. (3) Percentages are row percentages. Where they do not add to 100 this is due to rounding.

6.1.3 Devising models for specific client groups

The accuracy of profiling differs across client groups for a number of reasons. One is the differences in labour market and benefit claiming activity. JSA clients exhibit much greater attachment to the labour market than the sick and disabled and lone mothers. So, for example, over the period between ONE eligibility and the end of December 2002, JSA clients spent far less time claiming out-of-work benefits than the other two client groups (Table 6.2).

Table 6.2 Time spent claiming out-of-work benefits, ONE – 31 December 2002

	Sick and disabled	Lone mothers	JSA clients
Mean percentage time	70	67	30
Percentage spending all time	46	35	2

These differences in the distributions of outcomes can affect profiling accuracy, as discussed above. But we also show that profiling is more accurate when models are devised specifically for the client group, rather than using a profiling model devised for another client group. In some cases profiling accuracy increases when separate profiling models are devised for sub-groups within a client group, such as younger and older clients and men and women. But, in general, the gains from running profiling on sub-groups are small.

6.2 Some practical implications and future research

The study presents conclusive evidence that profiling outperforms random allocation of treatment, but wrong denial and wrong treatment rates are not trivial. However, it is difficult to judge whether the prediction rates reported here are sufficiently accurate to merit profiling as a resource allocation tool because we need to be able to compare success rates under profiling with those achieved through Personal Adviser discretion or the application of deterministic rules. Success rates for these alternative resource allocation mechanisms are not available. What we can say is that the data available for profiling make a substantial difference to the performance of profiling models. Fuller models performed better than parsimonious models, but how well fuller models perform depends on what is in those models. Variables that proved highly predictive of outcomes included benefit and work histories. These were only available to us in survey data form, and it is conceivable that administrative information on these matters would be the basis for better profiling. There is clearly a case for incorporating subjective information from clients. In our case, this was only available three to four months after ONE eligibility. If collected at the outset, information on work attitudes, perceived health status and care responsibilities may prove powerful indicators of what is likely to happen to clients in future.

As well as the comparison with alternative allocation methods, a number of other issues remained unresolved. Is statistical profiling a feasible option given the practical and ethical issues it raises? If so, what is the best way to implement profiling (who should do the profiling, using what data, and to what purpose)? How accurately could one predict benefit and labour market outcomes for new claims with data currently available? What resources should be devoted to the collection of additional information at the new claim interview to improve profiling?

In the longer term, if profiling is considered viable, further attention should be paid to:

- external validation of profiling models using a range of data sets;
- re-estimation of profiling models over real time and the business cycle;
- whether treatments have homogeneous or heterogeneous effects;
- the counterfactual: if profiling is introduced, will it lower average benefit durations or not? This depends on the appropriateness of treatment for those selected on profiling, and the response of the non-selected to non-treatment.

Appendix A
Models for sick and disabled clients

Table A.1 Guide to meaning of variable names used in the analyses for the sick and disabled

The list of variables and abbreviations used in the models for the sick and disabled (the reference categories are in bold).

Variable	Abbreviation
Gender- female *	fem
Age of respondent:	
- 18-24	**age1824**
- 25-29	age2529
- 30-34	age3034
- 35-39	age3539
- 40-44	age4044
- 45-49	age4549
- 50-54	age5054
- 55-60	age5560
Marital status:	
- single	**single**
- married	married
- cohabiting	cohab
- widowed	widowed
- divorced	divorced
- separated	separ

Continued

Table A.1 Continued

Variable	Abbreviation
Highest academic qualification obtained:	
- **None or no information**	**noqual**
- degree or equivalent	degree
- above A level-below degree	abovea
- A level or equivalent	alev
- GCSE A-C level or equivalent	gcseac
- GCSE D-E level or equivalnt	gcsede
- Foreign or other	foreign
Number of dependent children:	
- **one**	**onedkid**
- none	nodkid
- two	twodkid
- three or more	thrpdkid
Ethnicity – white*	white
Possesses telephone *	phoner
Licence and car/cycle access:	
- **has no licence**	**nolic**
- has licence but no car/cycle access	licnoveh
- has both	licandv
Long-standing illness disability:	
- **does not have**	**lsino**
- yes but has no affect on ability to work	lsinoaff
- yes and affects ability to work	lsiaff
- no information	lsidk
Mental disability*	mentdis
General health perceived:	
- **not good**	ghnotg
- good	ghgood
- fair	ghfair
Numeracy problems*	num
Literacy problems*	litr
Housing tenure:	
- **owner-occupation**	ownocc
- LA sector	rentla
- HA sector	rentha
- PRS	rentpriv
- other	tenoth
- institutions	tenin
Any time in last 2 years spent:*	
- unemployed	anyunemr
- temporary sick/disabled	anyillr
- long-term sick/disabled	anysickr
- in training	anytrair
- in education	anyeducr
- in other activity	anyothr
Number of workers in household excluding respondent:	
- **none**	hhwker0
- one	hhwker1
- two or more	hhwker2p

Continued

Table A.1 Continued

Variable	Abbreviation
Social class in last job before entry date:	
- **professional or intermediate**	**profint**
- skilled non-manual worker	skillnm
- skilled manual worker	skillman
- partly skilled manual	partskil
- unskilled manual	unskill
- no job or Armed Forces	nojarmed
Proportion of time working 1-15 hrs per week in 2 years pre – ONE:	
- **no time**	**pr150**
- up to half time	pr15150
- over half time	pr1550p
Proportion of time working 16+ hrs per week in 2 years pre – ONE:	
- **no time**	**pr160**
- up to 33% time	pr16133
- 34%-66% time	pr163466
- 67% to 99% time	pr166799
- all of time	pr16100
- No information	pr16dk
In receipt of benefits in 2 yr pre-ONE:	
- **none**	**nobben**
- out of work benefits only	oowbben
- in – work benefits only	inwbben
- both oow and in work benefits	bothbben
Net pay per week in pre-ONE job:	
- **<£100 pw**	**npu100**
- £100-£139 pw	np100139
- £140-189 pw	np140189
- £190-249 pw	np190249
- £250+ pw	np250p
- no job or no information	npdk
24 benefit/model type areas	
- **benefit area 1**	**_Ibenarea_1**
- benefit areas 2-24	_ibenarea_
6 benefit/model type area	
- **Basic/ONE**	**basicone**
- Basic/Control	basiccon
- Call Centre/ONE	callone
- Call Centre/Control	callcon
- PVS/ONE	pvsone
- PVS/Control	pvscon
Care responsibilities	
- **yes and affects work**	**careaff**
- yes but doesn't affect work	carenaff
- no responsibility or no information	nocare

Continued

Table A.1 Continued

Variable	Abbreviation
TTWA characteristics	
The unemployment rate in 1999	uerate99
The change in the unemployment rate (comparing the rate in January to March 1999 with the rate in January to March 2000)	uechange
The total number of claimants of Incapacity Benefit, Disability Living Allowance, Severe Disablement Allowance, and Income Support claimed with a Disability Premium expressed as a proportion of the total workforce	disabpc
The change in the disability total as a percentage of the workforce, comparing February 2000 and May 2000	chansick
Lone parents claiming Income Support (without a Disability Premium) as a proportion of the total workforce	lonepc
The change in this proportion between February 2000 and May 2000	chanlp
Attitude towards work	
- very negative	wavneg
- fairly negative	wafneg
- middling	wamid
- fairly positive	wafpos
- very positive	wavpos
Date of entry to ONE	dssdate

* These dummy variables are equal to 1 if true and 0 otherwise

Table A.2 Sick and disabled logistic regressions estimating whether out of work at wave 2

	(1) wv2nojob	(2) wv2nojob	(3) wv2nojob	(4) wv2nojob	(5) wv2nojob	(6) wv2nojob
fem	0.258	0.270	0.158	0.161	0.200	0.208
	(2.19)*	(2.25)*	(1.13)	(1.13)	(1.32)	(1.34)
age2529	0.335	0.352	0.301	0.299	0.368	0.346
	(1.32)	(1.39)	(1.13)	(1.12)	(1.20)	(1.12)
age3034	0.078	0.117	0.097	0.127	-0.027	-0.045
	(0.31)	(0.47)	(0.37)	(0.48)	(0.09)	(0.15)
age3539	0.280	0.262	0.314	0.282	0.221	0.160
	(1.11)	(1.03)	(1.15)	(1.02)	(0.72)	(0.51)
age4044	0.369	0.376	0.398	0.394	0.329	0.304
	(1.53)	(1.51)	(1.50)	(1.44)	(1.13)	(1.01)
age4549	0.532	0.601	0.530	0.588	0.485	0.546
	(2.18)*	(2.37)*	(1.92)	(2.07)*	(1.55)	(1.71)
age5054	0.905	0.973	0.912	0.989	0.903	0.998
	(3.70)**	(3.89)**	(3.20)**	(3.39)**	(2.81)**	(3.03)**
age5560	0.883	0.927	0.930	0.986	0.966	1.030
	(3.45)**	(3.56)**	(3.13)**	(3.25)**	(2.85)**	(3.00)**
white	-0.388	-0.441	-0.365	-0.426	-0.411	-0.522
	(1.47)	(1.59)	(1.34)	(1.49)	(1.43)	(1.72)
degree	-0.238	-0.261	-0.227	-0.248	-0.163	-0.199
	(1.00)	(1.09)	(0.89)	(0.97)	(0.66)	(0.78)
abovea	-0.672	-0.711	-0.615	-0.662	-0.437	-0.480
	(3.58)**	(3.67)**	(3.15)**	(3.30)**	(2.10)*	(2.26)*
alev	-0.574	-0.617	-0.561	-0.612	-0.455	-0.497
	(2.75)**	(2.91)**	(2.61)**	(2.78)**	(1.95)	(2.12)*
gcseac	-0.355	-0.353	-0.307	-0.306	-0.152	-0.140
	(2.22)*	(2.20)*	(1.86)	(1.84)	(0.86)	(0.79)
gcsede	-0.503	-0.453	-0.537	-0.484	-0.380	-0.312
	(2.36)*	(2.13)*	(2.49)*	(2.25)*	(1.64)	(1.33)
foreign	-0.372	-0.423	-0.358	-0.409	-0.338	-0.400
	(1.62)	(1.83)	(1.53)	(1.74)	(1.33)	(1.54)
num	0.748	0.760	0.672	0.690	0.352	0.363
	(2.65)**	(2.61)**	(2.36)*	(2.36)*	(1.14)	(1.14)
litr	0.365	0.430	0.359	0.429	0.266	0.364
	(1.46)	(1.67)	(1.40)	(1.61)	(1.00)	(1.33)
rentla	0.695	0.719	0.699	0.738	0.342	0.399
	(4.42)**	(4.54)**	(4.21)**	(4.42)**	(1.86)	(2.14)*
rentha	0.296	0.361	0.294	0.361	0.033	0.075
	(1.27)	(1.52)	(1.21)	(1.46)	(0.12)	(0.29)
rentpriv	0.840	0.904	0.868	0.938	0.657	0.747
	(4.02)**	(4.24)**	(4.00)**	(4.27)**	(2.78)**	(3.07)**
tenoth	0.575	0.663	0.435	0.529	0.760	0.911
	(3.06)**	(3.41)**	(1.97)*	(2.35)*	(2.93)**	(3.46)**
tenin	0.741	0.843	0.504	0.619	-0.052	0.015
	(1.07)	(1.13)	(0.77)	(0.89)	(0.07)	(0.02)
oowbben	0.117	0.100	0.059	0.041	-0.144	-0.179
	(0.67)	(0.58)	(0.32)	(0.23)	(0.74)	(0.93)
inwbben	-0.498	-0.548	-0.546	-0.605	-0.730	-0.805
	(2.64)**	(2.86)**	(2.74)**	(3.00)**	(3.25)**	(3.55)**
bothbben	0.198	0.153	0.171	0.115	-0.264	-0.290
	(0.72)	(0.56)	(0.59)	(0.40)	(0.81)	(0.90)

Continued

Table A.2 Continued

	(1) wv2nojob	(2) wv2nojob	(3) wv2nojob	(4) wv2nojob	(5) wv2nojob	(6) wv2nojob
disabpc	-0.017	-0.091	-0.018	-0.104	-0.002	-0.115
	(0.87)	(2.09)*	(0.90)	(2.30)*	(0.08)	(2.41)*
chansick	0.182	0.732	0.191	0.771	-0.011	0.688
	(0.58)	(1.86)	(0.60)	(1.91)	(0.03)	(1.46)
lonepc	0.085	0.332	0.093	0.341	0.116	0.417
	(0.73)	(1.94)	(0.80)	(2.01)*	(0.89)	(2.22)*
chanlp	0.465	0.762	0.454	0.820	0.778	1.059
	(0.96)	(1.31)	(0.92)	(1.38)	(1.43)	(1.61)
uerate99	0.010	-0.094	0.008	-0.087	-0.025	-0.119
	(0.21)	(1.12)	(0.15)	(1.02)	(0.44)	(1.26)
uechange	-0.269	-0.467	-0.300	-0.523	-0.000	-0.120
	(1.11)	(1.46)	(1.23)	(1.63)	(0.00)	(0.34)
basiccon	0.694		0.683		0.720	
	(3.29)**		(3.19)**		(2.98)**	
callone	0.328		0.293		0.377	
	(1.69)		(1.49)		(1.80)	
callcon	0.117		0.070		0.163	
	(0.59)		(0.35)		(0.77)	
pvsone	0.166		0.179		0.206	
	(0.86)		(0.91)		(1.00)	
pvscon	0.690		0.694		0.725	
	(3.30)**		(3.25)**		(3.12)**	
pr16133	-0.906	-0.943	-0.692	-0.702	-0.417	-0.432
	(3.01)**	(3.12)**	(2.27)*	(2.29)*	(1.23)	(1.28)
pr163466	-1.563	-1.552	-1.393	-1.369	-1.046	-1.012
	(5.95)**	(5.89)**	(5.11)**	(5.00)**	(3.49)**	(3.37)**
pr166799	-2.055	-2.091	-1.905	-1.928	-1.666	-1.689
	(8.43)**	(8.64)**	(7.28)**	(7.52)**	(5.73)**	(5.96)**
pr16100	-2.550	-2.573	-2.595	-2.588	-2.461	-2.472
	(9.84)**	(10.02)**	(7.95)**	(8.02)**	(6.91)**	(7.08)**
pr16dk	-1.914	-1.886	-1.993	-1.947	-1.874	-1.841
	(7.44)**	(7.35)**	(6.09)**	(5.96)**	(5.37)**	(5.32)**
pr15150	0.518	0.541	0.406	0.401	0.589	0.583
	(1.17)	(1.17)	(0.92)	(0.88)	(1.25)	(1.22)
pr1550p	-2.289	-2.355	-2.308	-2.359	-2.349	-2.380
	(6.19)**	(6.39)**	(5.76)**	(5.92)**	(5.58)**	(5.63)**
anyunemr	-0.389	-0.351	-0.511	-0.451	-0.534	-0.486
	(2.16)*	(1.96)	(2.31)*	(2.03)*	(2.27)*	(2.10)*
_Ibenarea_2		0.439		0.345		0.317
		(0.93)		(0.72)		(0.64)
_Ibenarea_3		1.532		1.540		1.679
		(2.37)*		(2.32)*		(2.32)*
_Ibenarea_4		0.044		-0.161		-0.328
		(0.10)		(0.36)		(0.70)
_Ibenarea_5		0.442		0.291		0.400
		(0.90)		(0.59)		(0.76)
_Ibenarea_6		0.656		0.506		0.413
		(1.31)		(0.99)		(0.78)
_Ibenarea_7		1.582		1.554		1.957
		(2.59)**		(2.47)*		(2.87)**

Continued

Table A.2 Continued

	(1) wv2nojob	(2) wv2nojob	(3) wv2nojob	(4) wv2nojob	(5) wv2nojob	(6) wv2nojob
_Ibenarea_8		0.754		0.653		0.633
		(1.72)		(1.45)		(1.35)
_Ibenarea_9		0.265		0.142		0.045
		(0.57)		(0.30)		(0.09)
_Ibenarea_10		1.449		1.476		1.669
		(2.21)*		(2.21)*		(2.30)*
_Ibenarea_11		1.006		0.916		0.760
		(2.22)*		(2.00)*		(1.61)
_Ibenarea_12		0.723		0.718		0.997
		(1.35)		(1.31)		(1.75)
_Ibenarea_13		0.295		0.147		-0.193
		(0.62)		(0.31)		(0.38)
_Ibenarea_14		0.663		0.533		0.664
		(1.29)		(1.02)		(1.16)
_Ibenarea_15		2.506		2.442		2.711
		(4.20)**		(4.07)**		(4.07)**
_Ibenarea_16		1.280		1.235		1.267
		(2.72)**		(2.57)*		(2.53)*
_Ibenarea_17		0.153		-0.034		-0.008
		(0.31)		(0.07)		(0.01)
_Ibenarea_18		0.628		0.476		0.570
		(1.35)		(1.01)		(1.15)
_Ibenarea_19		0.715		0.593		0.484
		(1.45)		(1.19)		(0.95)
_Ibenarea_20		0.583		0.425		0.603
		(1.21)		(0.86)		(1.18)
_Ibenarea_21		1.047		0.954		0.869
		(2.21)*		(2.00)*		(1.75)
_Ibenarea_22		1.337		1.369		1.446
		(2.35)*		(2.34)*		(2.35)*
_Ibenarea_23		1.918		1.830		2.126
		(3.39)**		(3.18)**		(3.42)**
_Ibenarea_24		1.565		1.446		1.749
		(2.76)**		(2.50)*		(2.64)**
married			-0.183	-0.199	0.030	0.003
			(0.92)	(0.98)	(0.13)	(0.01)
cohab			-0.412	-0.433	-0.261	-0.285
			(1.65)	(1.69)	(0.92)	(1.00)
widowed			-0.745	-0.860	-0.875	-0.979
			(1.66)	(1.98)*	(2.01)*	(2.25)*
divorced			-0.325	-0.331	-0.519	-0.548
			(1.45)	(1.45)	(2.20)*	(2.25)*
separ			0.149	0.141	-0.047	-0.050
			(0.49)	(0.46)	(0.14)	(0.15)
nodkid			-0.207	-0.248	-0.392	-0.473
			(1.09)	(1.29)	(1.95)	(2.29)*
twodkid			-0.455	-0.469	-0.490	-0.537
			(2.07)*	(2.11)*	(2.09)*	(2.23)*
thrpdkid			-0.270	-0.264	-0.106	-0.108
			(0.91)	(0.90)	(0.32)	(0.33)
anyillr			-0.089	-0.085	-0.317	-0.336
			(0.44)	(0.41)	(1.44)	(1.51)

Continued

Table A.2 Continued

	(1) wv2nojob	(2) wv2nojob	(3) wv2nojob	(4) wv2nojob	(5) wv2nojob	(6) wv2nojob
anysickr			0.056	0.111	-0.404	-0.338
			(0.16)	(0.33)	(1.12)	(0.94)
anytrair			0.313	0.249	0.499	0.475
			(0.66)	(0.53)	(0.99)	(0.96)
anyeducr			-0.601	-0.624	-0.501	-0.556
			(1.61)	(1.61)	(1.30)	(1.42)
anyothr			-0.526	-0.510	-0.527	-0.533
			(1.98)*	(1.88)	(1.82)	(1.80)
np100139			-0.295	-0.322	-0.489	-0.517
			(1.46)	(1.58)	(2.17)*	(2.26)*
np140189			-0.167	-0.188	-0.250	-0.255
			(0.84)	(0.94)	(1.15)	(1.16)
np190249			-0.214	-0.223	-0.271	-0.281
			(0.97)	(0.99)	(1.11)	(1.14)
np250p			-0.257	-0.287	-0.225	-0.246
			(1.21)	(1.34)	(0.98)	(1.04)
npdk			-0.182	-0.223	-0.279	-0.307
			(0.63)	(0.76)	(0.88)	(0.96)
skillnm			0.079	0.101	0.096	0.084
			(0.40)	(0.50)	(0.46)	(0.39)
skillman			-0.104	-0.110	-0.031	-0.046
			(0.58)	(0.60)	(0.16)	(0.23)
partskil			0.086	0.072	0.150	0.118
			(0.47)	(0.39)	(0.74)	(0.56)
unskill			-0.192	-0.245	-0.179	-0.253
			(0.75)	(0.94)	(0.64)	(0.87)
nojarmed			0.475	0.510	0.652	0.654
			(1.47)	(1.56)	(1.86)	(1.86)
dssdate			-0.002	-0.002	0.001	0.001
			(0.96)	(0.92)	(0.22)	(0.36)
ghfair					-0.714	-0.733
					(4.61)**	(4.69)**
ghgood					-0.558	-0.586
					(2.90)**	(2.94)**
lsinoaff					-0.252	-0.199
					(1.11)	(0.86)
lsiaff					0.927	0.974
					(5.85)**	(5.99)**
lsidk					0.824	0.761
					(0.70)	(0.69)
mentdis					0.307	0.339
					(1.82)	(1.99)*
carenaff					-0.598	-0.676
					(2.30)*	(2.55)*
nocare					-0.315	-0.312
					(1.34)	(1.30)
phoner					-0.556	-0.484
					(1.25)	(1.09)
licnoveh					-0.151	-0.224
					(0.64)	(0.95)
licandv					-0.721	-0.731
					(4.59)**	(4.52)**

Continued

Table A.2 Continued

	(1) wv2nojob	(2) wv2nojob	(3) wv2nojob	(4) wv2nojob	(5) wv2nojob	(6) wv2nojob
hhwker1					-0.675	-0.685
					(4.35)**	(4.45)**
hhwker2p					-0.816	-0.875
					(3.87)**	(4.12)**
wafneg					-0.266	-0.296
					(1.31)	(1.44)
wamid					0.081	0.104
					(0.42)	(0.52)
wafpos					-0.190	-0.217
					(1.04)	(1.17)
wavpos					-0.477	-0.519
					(2.68)**	(2.85)**
Constant	1.784	1.678	34.304	32.901	-3.365	-7.940
	(3.41)**	(2.30)*	(1.03)	(1.00)	(0.10)	(0.23)
Observations	2134	2134	2134	2134	2134	2134

Table A.3 Logit estimates for out-of-work benefit receipt twelve months after their claim for benefit, sick and disabled clients

	(1) wv2oowbr	(2) wv2oowbr	(3) wv2oowbr	(4) wv2oowbr	(5) wv2oowbr	(6) wv2oowbr
fem	-0.020	-0.033	-0.179	-0.203	-0.184	-0.205
	(0.18)	(0.29)	(1.34)	(1.49)	(1.28)	(1.39)
age2529	0.348	0.354	0.276	0.278	0.210	0.197
	(1.48)	(1.48)	(1.09)	(1.09)	(0.73)	(0.68)
age3034	0.140	0.150	0.055	0.061	-0.254	-0.251
	(0.59)	(0.63)	(0.22)	(0.24)	(0.86)	(0.85)
age3539	0.360	0.366	0.243	0.254	-0.055	-0.046
	(1.58)	(1.60)	(0.95)	(0.98)	(0.19)	(0.16)
age4044	0.526	0.539	0.368	0.387	0.197	0.217
	(2.25)*	(2.30)*	(1.44)	(1.51)	(0.69)	(0.75)
age4549	0.793	0.849	0.620	0.680	0.413	0.466
	(3.42)**	(3.63)**	(2.30)*	(2.49)*	(1.38)	(1.54)
age5054	0.853	0.892	0.687	0.735	0.421	0.470
	(3.77)**	(3.93)**	(2.54)*	(2.68)**	(1.39)	(1.53)
age5560	0.850	0.878	0.712	0.758	0.492	0.552
	(3.57)**	(3.65)**	(2.50)*	(2.63)**	(1.50)	(1.65)
white	-0.330	-0.353	-0.337	-0.376	-0.384	-0.444
	(1.26)	(1.27)	(1.27)	(1.33)	(1.34)	(1.44)
degree	-0.318	-0.312	-0.276	-0.270	-0.201	-0.211
	(1.41)	(1.38)	(1.14)	(1.11)	(0.79)	(0.83)
abovea	-0.704	-0.723	-0.667	-0.681	-0.555	-0.549
	(4.01)**	(4.07)**	(3.59)**	(3.62)**	(2.81)**	(2.73)**
alev	-0.373	-0.406	-0.322	-0.358	-0.228	-0.262
	(1.90)	(2.04)*	(1.57)	(1.73)	(0.99)	(1.12)
gcseac	-0.189	-0.198	-0.160	-0.165	-0.104	-0.092
	(1.27)	(1.32)	(1.03)	(1.06)	(0.62)	(0.55)
gcsede	-0.190	-0.193	-0.260	-0.268	-0.199	-0.180
	(0.94)	(0.95)	(1.28)	(1.31)	(0.95)	(0.86)

Continued

Table A.3 Continued

	(1) wv2oowbr	(2) wv2oowbr	(3) wv2oowbr	(4) wv2oowbr	(5) wv2oowbr	(6) wv2oowbr
foreign	-0.582	-0.601	-0.627	-0.650	-0.639	-0.654
	(2.92)**	(3.00)**	(3.03)**	(3.11)**	(2.82)**	(2.84)**
num	0.630	0.610	0.624	0.610	0.445	0.423
	(2.72)**	(2.58)*	(2.67)**	(2.55)*	(1.73)	(1.62)
litr	0.073	0.115	0.011	0.054	-0.162	-0.109
	(0.36)	(0.56)	(0.05)	(0.26)	(0.69)	(0.45)
rentla	0.647	0.638	0.519	0.506	0.095	0.081
	(4.49)**	(4.39)**	(3.32)**	(3.20)**	(0.54)	(0.46)
rentha	1.122	1.136	1.015	1.019	0.678	0.682
	(4.69)**	(4.78)**	(4.10)**	(4.14)**	(2.54)*	(2.54)*
rentpriv	1.142	1.194	1.074	1.121	0.736	0.786
	(5.15)**	(5.34)**	(4.59)**	(4.79)**	(3.04)**	(3.22)**
tenoth	0.572	0.641	0.212	0.272	0.239	0.305
	(3.14)**	(3.45)**	(0.99)	(1.25)	(0.97)	(1.22)
tenin	0.855	0.840	0.522	0.506	-0.000	0.010
	(1.58)	(1.53)	(0.90)	(0.85)	(0.00)	(0.01)
oowbben	0.466	0.439	0.360	0.329	0.285	0.249
	(3.04)**	(2.85)**	(2.25)*	(2.03)*	(1.66)	(1.43)
inwbben	-0.113	-0.084	-0.122	-0.090	-0.203	-0.164
	(0.63)	(0.46)	(0.65)	(0.47)	(1.03)	(0.83)
bothbben	0.399	0.375	0.286	0.264	-0.055	-0.076
	(1.63)	(1.54)	(1.12)	(1.03)	(0.20)	(0.27)
disabpc	-0.018	-0.088	-0.014	-0.090	-0.005	-0.092
	(0.98)	(2.13)*	(0.75)	(2.16)*	(0.22)	(2.00)*
chansick	0.408	0.568	0.361	0.536	0.151	0.344
	(1.35)	(1.68)	(1.18)	(1.57)	(0.44)	(0.88)
lonepc	0.215	0.545	0.170	0.508	0.190	0.579
	(1.86)	(3.38)**	(1.43)	(3.07)**	(1.47)	(3.20)**
chanlp	-0.666	-0.117	-0.779	-0.199	-0.400	0.194
	(1.45)	(0.22)	(1.65)	(0.37)	(0.76)	(0.30)
uerate99	-0.014	-0.101	-0.002	-0.089	-0.040	-0.156
	(0.29)	(1.25)	(0.04)	(1.09)	(0.74)	(1.75)
uechange	0.125	-0.034	0.147	-0.023	0.300	0.147
	(0.54)	(0.12)	(0.62)	(0.08)	(1.14)	(0.44)
basiccon	-0.011		-0.040		-0.081	
	(0.06)		(0.20)		(0.37)	
callone	0.333		0.303		0.402	
	(1.74)		(1.55)		(1.92)	
callcon	-0.051		-0.052		0.037	
	(0.26)		(0.26)		(0.17)	
pvsone	0.111		0.109		0.102	
	(0.60)		(0.58)		(0.51)	
pvscon	0.772		0.780		0.834	
	(3.84)**		(3.82)**		(3.85)**	
pr16133	-0.736	-0.747	-0.579	-0.586	-0.298	-0.315
	(3.09)**	(3.09)**	(2.30)*	(2.29)*	(1.10)	(1.15)
pr163466	-1.245	-1.267	-1.145	-1.170	-0.856	-0.877
	(5.84)**	(5.89)**	(5.01)**	(5.07)**	(3.34)**	(3.35)**
pr166799	-1.071	-1.090	-1.107	-1.130	-0.888	-0.925
	(5.58)**	(5.62)**	(5.19)**	(5.27)**	(3.83)**	(3.94)**
pr16100	-1.156	-1.211	-1.665	-1.729	-1.411	-1.491
	(5.56)**	(5.75)**	(6.00)**	(6.22)**	(4.78)**	(5.00)**

Continued

Table A.3 Continued

	(1) wv2oowbr	(2) wv2oowbr	(3) wv2oowbr	(4) wv2oowbr	(5) wv2oowbr	(6) wv2oowbr
pr16dk	-1.283	-1.310	-1.800	-1.837	-1.662	-1.717
	(5.93)**	(5.93)**	(6.34)**	(6.43)**	(5.47)**	(5.59)**
pr15150	0.765	0.771	0.555	0.551	0.568	0.562
	(2.15)*	(2.11)*	(1.50)	(1.45)	(1.41)	(1.37)
pr1550p	-1.556	-1.577	-1.972	-1.996	-1.950	-1.992
	(4.69)**	(4.74)**	(5.37)**	(5.40)**	(5.16)**	(5.26)**
anyunemr	-0.364	-0.354	-0.689	-0.679	-0.663	-0.664
	(2.33)*	(2.26)*	(3.50)**	(3.40)**	(3.14)**	(3.13)**
_Ibenarea_2		0.888		0.846		0.914
		(1.93)		(1.83)		(1.81)
_Ibenarea_3		1.493		1.482		1.578
		(2.43)*		(2.38)*		(2.21)*
_Ibenarea_4		0.307		0.259		0.096
		(0.67)		(0.53)		(0.19)
_Ibenarea_5		1.033		1.007		1.034
		(2.15)*		(2.05)*		(1.97)*
_Ibenarea_6		0.934		0.776		0.853
		(1.90)		(1.58)		(1.57)
_Ibenarea_7		1.402		1.398		1.548
		(2.38)*		(2.36)*		(2.37)*
_Ibenarea_8		0.968		0.894		1.020
		(2.23)*		(1.99)*		(2.12)*
_Ibenarea_9		0.716		0.660		0.652
		(1.59)		(1.43)		(1.25)
_Ibenarea_10		1.466		1.521		1.564
		(2.40)*		(2.46)*		(2.24)*
_Ibenarea_11		0.916		0.834		0.710
		(2.10)*		(1.85)		(1.47)
_Ibenarea_12		1.058		1.053		1.277
		(2.05)*		(2.00)*		(2.18)*
_Ibenarea_13		0.370		0.218		-0.043
		(0.83)		(0.47)		(0.09)
_Ibenarea_14		0.517		0.477		0.334
		(1.06)		(0.95)		(0.60)
_Ibenarea_15		1.263		1.266		1.441
		(2.41)*		(2.36)*		(2.32)*
_Ibenarea_16		0.654		0.581		0.581
		(1.42)		(1.23)		(1.15)
_Ibenarea_17		0.376		0.226		0.209
		(0.79)		(0.46)		(0.39)
_Ibenarea_18		0.257		0.206		0.274
		(0.55)		(0.43)		(0.55)
_Ibenarea_19		1.270		1.281		1.315
		(2.68)**		(2.60)**		(2.50)*
_Ibenarea_20		0.432		0.389		0.620
		(0.91)		(0.80)		(1.19)
_Ibenarea_21		1.339		1.312		1.200
		(2.86)**		(2.76)**		(2.40)*
_Ibenarea_22		1.830		1.861		1.985
		(3.33)**		(3.35)**		(3.29)**
_Ibenarea_23		1.886		1.830		2.043
		(3.57)**		(3.38)**		(3.46)**

Continued

Table A.3 Continued

	(1) wv2oowbr	(2) wv2oowbr	(3) wv2oowbr	(4) wv2oowbr	(5) wv2oowbr	(6) wv2oowbr
_Ibenarea_24		1.707		1.742		2.048
		(3.11)**		(3.04)**		(3.26)**
married			-0.471	-0.500	-0.261	-0.304
			(2.41)*	(2.52)*	(1.15)	(1.33)
cohab			-0.830	-0.850	-0.764	-0.776
			(3.42)**	(3.45)**	(2.80)**	(2.82)**
widowed			-0.213	-0.264	-0.186	-0.225
			(0.48)	(0.58)	(0.38)	(0.44)
divorced			-0.180	-0.175	-0.286	-0.288
			(0.79)	(0.76)	(1.18)	(1.17)
separ			0.160	0.151	-0.033	-0.018
			(0.55)	(0.51)	(0.11)	(0.06)
nodkid			-0.349	-0.390	-0.522	-0.587
			(1.91)	(2.10)*	(2.74)**	(3.00)**
twodkid			-0.688	-0.729	-0.734	-0.801
			(3.20)**	(3.38)**	(3.20)**	(3.44)**
thrpdkid			-0.350	-0.381	-0.220	-0.255
			(1.31)	(1.41)	(0.75)	(0.87)
anyillr			-0.271	-0.277	-0.418	-0.422
			(1.51)	(1.52)	(2.12)*	(2.11)*
anysickr			-0.218	-0.193	-0.557	-0.532
			(0.80)	(0.70)	(1.87)	(1.77)
anytrair			-0.260	-0.304	-0.260	-0.303
			(0.67)	(0.77)	(0.60)	(0.68)
anyeducr			-1.048	-1.058	-1.184	-1.192
			(3.56)**	(3.54)**	(3.62)**	(3.59)**
anyothr			-1.176	-1.198	-1.243	-1.283
			(4.64)**	(4.68)**	(4.43)**	(4.52)**
np100139			-0.094	-0.083	-0.202	-0.183
			(0.49)	(0.43)	(0.98)	(0.88)
np140189			-0.087	-0.083	-0.014	-0.008
			(0.47)	(0.45)	(0.07)	(0.04)
np190249			-0.029	-0.056	0.041	0.007
			(0.14)	(0.26)	(0.18)	(0.03)
np250p			-0.305	-0.307	-0.166	-0.162
			(1.54)	(1.54)	(0.77)	(0.75)
npdk			-0.130	-0.134	-0.009	-0.030
			(0.50)	(0.51)	(0.03)	(0.11)
skillnm			-0.210	-0.183	-0.192	-0.164
			(1.03)	(0.89)	(0.90)	(0.76)
skillman			-0.151	-0.143	-0.073	-0.061
			(0.83)	(0.78)	(0.36)	(0.31)
partskil			-0.244	-0.240	-0.264	-0.257
			(1.31)	(1.28)	(1.29)	(1.25)
unskill			-0.068	-0.056	0.013	0.026
			(0.28)	(0.23)	(0.05)	(0.09)
nojarmed			0.191	0.184	0.190	0.182
			(0.64)	(0.61)	(0.59)	(0.57)
dssdate			-0.002	-0.002	-0.002	-0.002
			(1.00)	(1.03)	(0.78)	(0.73)

Continued

Table A.3 Continued

	(1) wv2oowbr	(2) wv2oowbr	(3) wv2oowbr	(4) wv2oowbr	(5) wv2oowbr	(6) wv2oowbr
ghfair					-0.740	-0.746
					(5.00)**	(5.00)**
ghgood					-0.644	-0.646
					(3.56)**	(3.53)**
lsinoaff					-0.241	-0.215
					(1.13)	(0.99)
lsiaff					0.740	0.765
					(4.95)**	(5.03)**
lsidk					-0.897	-0.649
					(0.83)	(0.61)
mentdis					0.336	0.350
					(2.09)*	(2.17)*
carenaff					-0.935	-0.978
					(3.42)**	(3.54)**
nocare					-0.965	-0.983
					(3.80)**	(3.84)**
phoner					-0.008	0.071
					(0.02)	(0.20)
licnoveh					-0.558	-0.570
					(2.61)**	(2.65)**
licandv					-0.862	-0.867
					(5.71)**	(5.60)**
hhwker1					-0.636	-0.646
					(4.35)**	(4.39)**
hhwker2p					-0.748	-0.792
					(3.52)**	(3.72)**
wafneg					0.134	0.130
					(0.69)	(0.67)
wamid					0.085	0.075
					(0.46)	(0.40)
wafpos					-0.146	-0.144
					(0.85)	(0.84)
wavpos					-0.289	-0.281
					(1.74)	(1.68)
Constant	0.512	-0.158	37.210	34.997	37.714	32.251
	(1.11)	(0.24)	(1.06)	(1.08)	(0.87)	(0.82)
Observations	2128	2128	2128	2128	2128	2128

Table A.4 OLS estimates of percentage of time on benefit, ONE eligibility-31/12/02

	(1) pcben1	(2) pcben2	(3) pcben3	(4) Pcben4	(5) pcben5	(6) pcben6
fem	0.861	0.870	-2.009	-2.080	-2.069	-2.241
	(0.70)	(0.70)	(1.45)	(1.51)	(1.55)	(1.67)
age2529	0.446	0.439	0.687	0.643	-1.199	-1.171
	(0.18)	(0.18)	(0.28)	(0.26)	(0.50)	(0.49)
age3034	1.122	0.921	2.049	1.843	-1.081	-1.169
	(0.46)	(0.37)	(0.80)	(0.72)	(0.44)	(0.48)
age3539	2.796	2.540	3.606	3.390	-0.813	-0.931
	(1.16)	(1.05)	(1.42)	(1.33)	(0.34)	(0.38)
age4044	7.350	7.095	7.336	7.087	3.260	2.965
	(2.97)**	(2.85)**	(2.79)**	(2.69)**	(1.31)	(1.18)
age4549	10.609	10.451	9.500	9.373	4.794	4.710
	(4.33)**	(4.24)**	(3.56)**	(3.49)**	(1.88)	(1.83)
age5054	13.564	13.421	12.235	12.140	8.221	8.089
	(5.70)**	(5.62)**	(4.55)**	(4.49)**	(3.18)**	(3.12)**
age5560	15.154	15.081	13.943	13.919	10.342	10.244
	(6.26)**	(6.20)**	(5.00)**	(4.95)**	(3.87)**	(3.80)**
white	-2.138	-1.910	-2.228	-2.251	-1.008	-1.186
	(1.01)	(0.87)	(1.05)	(1.03)	(0.51)	(0.57)
degree	-4.864	-4.942	-4.436	-4.436	-5.554	-5.622
	(1.76)	(1.79)	(1.55)	(1.56)	(2.08)*	(2.12)*
abovea	-6.231	-6.213	-5.259	-5.212	-3.824	-3.712
	(3.02)**	(3.02)**	(2.53)*	(2.51)*	(1.95)	(1.89)
alev	-5.473	-5.419	-5.651	-5.545	-3.915	-3.745
	(2.57)*	(2.54)*	(2.66)**	(2.60)**	(2.00)*	(1.90)
gcseac	-4.261	-3.908	-4.171	-3.820	-3.149	-2.811
	(2.56)*	(2.33)*	(2.49)*	(2.27)*	(2.03)*	(1.80)
gcsede	-4.522	-4.407	-4.438	-4.340	-2.511	-2.424
	(2.05)*	(1.99)*	(2.06)*	(2.01)*	(1.23)	(1.18)
foreign	-3.077	-2.833	-3.519	-3.250	-4.356	-4.104
	(1.39)	(1.28)	(1.58)	(1.46)	(2.02)*	(1.92)
num	6.300	6.450	5.675	5.817	4.044	4.141
	(3.22)**	(3.29)**	(2.96)**	(3.03)**	(2.20)*	(2.25)*
litr	3.158	3.129	2.286	2.299	1.465	1.475
	(1.74)	(1.72)	(1.28)	(1.28)	(0.83)	(0.84)
rentla	15.604	15.503	13.962	13.833	9.463	9.312
	(9.65)**	(9.54)**	(8.43)**	(8.30)**	(5.92)**	(5.79)**
rentha	18.570	18.831	16.377	16.519	11.151	11.144
	(8.47)**	(8.55)**	(7.21)**	(7.23)**	(5.14)**	(5.11)**
rentpriv	18.638	18.475	16.149	15.985	10.773	10.481
	(9.33)**	(9.24)**	(7.88)**	(7.80)**	(5.57)**	(5.42)**
tenoth	9.986	9.875	3.958	3.872	5.579	5.375
	(4.94)**	(4.88)**	(1.79)	(1.74)	(2.56)*	(2.46)*
tenin	19.814	19.764	13.101	13.185	9.099	8.794
	(5.02)**	(4.88)**	(3.26)**	(3.20)**	(2.42)*	(2.31)*
oowbben	10.933	10.984	8.478	8.524	6.616	6.669
	(6.40)**	(6.43)**	(4.84)**	(4.86)**	(4.07)**	(4.09)**
inwbben	1.180	1.326	0.821	0.952	-0.863	-0.884
	(0.44)	(0.49)	(0.31)	(0.35)	(0.35)	(0.36)
bothbben	9.540	9.547	8.542	8.554	4.405	4.461
	(3.30)**	(3.30)**	(2.96)**	(2.96)**	(1.62)	(1.63)

Continued

Table A.4 Continued

	(1) pcben1	(2) pcben2	(3) pcben3	(4) Pcben4	(5) pcben5	(6) pcben6
disabpc	-0.123	-0.284	-0.180	-0.410	0.075	-0.025
	(0.60)	(0.62)	(0.88)	(0.91)	(0.40)	(0.06)
chansick	1.165	4.382	1.831	5.000	1.058	4.312
	(0.35)	(1.25)	(0.56)	(1.42)	(0.35)	(1.33)
lonepc	2.300	1.992	2.259	2.166	1.509	1.559
	(1.84)	(1.12)	(1.80)	(1.22)	(1.28)	(0.95)
chanlp	0.117	1.712	1.458	3.541	1.196	1.505
	(0.02)	(0.27)	(0.26)	(0.57)	(0.23)	(0.26)
uerate99	0.256	0.154	0.373	0.312	0.132	-0.278
	(0.50)	(0.18)	(0.73)	(0.36)	(0.28)	(0.36)
uechange	-3.577	-2.619	-3.422	-2.678	-3.175	-1.901
	(1.40)	(0.83)	(1.34)	(0.85)	(1.36)	(0.66)
basiccon	5.284		5.247		5.481	
	(2.60)**		(2.63)**		(2.91)**	
callone	6.192		6.073		6.835	
	(2.95)**		(2.95)**		(3.55)**	
callcon	1.457		1.315		2.670	
	(0.67)		(0.61)		(1.33)	
pvsone	2.653		2.318		2.630	
	(1.24)		(1.11)		(1.34)	
pvscon	5.676		6.011		5.402	
	(2.64)**		(2.84)**		(2.71)**	
pr16133	-10.680	-10.563	-6.702	-6.654	-2.507	-2.562
	(4.82)**	(4.76)**	(3.00)**	(2.97)**	(1.19)	(1.21)
pr163466	-13.239	-13.028	-9.047	-8.879	-4.608	-4.377
	(6.15)**	(6.08)**	(4.09)**	(4.02)**	(2.24)*	(2.13)*
pr166799	-14.501	-14.597	-9.750	-9.925	-4.990	-5.105
	(7.25)**	(7.33)**	(4.60)**	(4.69)**	(2.48)*	(2.53)*
pr16100	-16.813	-16.745	-10.936	-10.938	-6.097	-6.011
	(7.73)**	(7.70)**	(4.02)**	(4.04)**	(2.41)*	(2.38)*
pr16dk	-15.130	-14.929	-10.069	-9.950	-8.815	-8.794
	(7.12)**	(7.01)**	(3.78)**	(3.74)**	(3.53)**	(3.52)**
pr15150	-3.728	-3.698	-2.724	-2.796	-0.550	-0.516
	(0.87)	(0.86)	(0.63)	(0.65)	(0.14)	(0.13)
pr1550p	-17.427	-17.104	-14.684	-14.601	-9.311	-8.849
	(3.87)**	(3.82)**	(3.20)**	(3.20)**	(2.29)*	(2.17)*
anyunemr	-5.053	-4.891	-1.898	-1.760	-1.211	-1.101
	(3.47)**	(3.33)**	(1.02)	(0.95)	(0.70)	(0.63)
_Ibenarea_10		5.219		4.548		4.816
		(0.84)		(0.74)		(0.86)
_Ibenarea_11		3.853		2.486		1.305
		(0.88)		(0.58)		(0.33)
_Ibenarea_12		1.923		1.540		3.194
		(0.34)		(0.28)		(0.62)
_Ibenarea_13		5.706		4.528		5.491
		(1.30)		(1.05)		(1.34)
_Ibenarea_14		-1.671		-1.304		-0.127
		(0.31)		(0.25)		(0.03)
_Ibenarea_15		10.927		10.141		11.077
		(2.01)*		(1.88)		(2.23)*
_Ibenarea_16		5.439		4.117		3.104
		(1.23)		(0.95)		(0.77)

Continued

Table A.4 Continued

	(1) pcben1	(2) pcben2	(3) pcben3	(4) Pcben4	(5) pcben5	(6) pcben6
_Ibenarea_17		1.501		0.442		-0.727
		(0.30)		(0.09)		(0.16)
_Ibenarea_18		-0.613		-1.829		1.097
		(0.13)		(0.40)		(0.26)
_Ibenarea_19		-1.587		-2.064		-0.800
		(0.32)		(0.42)		(0.18)
_Ibenarea_20		4.468		2.855		6.230
		(0.95)		(0.61)		(1.43)
_Ibenarea_21		6.342		5.322		4.852
		(1.36)		(1.15)		(1.13)
_Ibenarea_22		7.420		7.811		5.711
		(1.32)		(1.42)		(1.12)
_Ibenarea_23		5.526		4.752		5.237
		(1.02)		(0.89)		(1.05)
_Ibenarea_24		5.957		5.235		6.218
		(1.31)		(1.16)		(1.48)
_Ibenarea_2		0.254		-0.604		0.137
		(0.05)		(0.12)		(0.03)
_Ibenarea_3		2.059		1.453		0.465
		(0.32)		(0.23)		(0.08)
_Ibenarea_4		0.592		-1.393		-0.769
		(0.14)		(0.33)		(0.19)
_Ibenarea_5		0.670		-0.118		1.082
		(0.14)		(0.02)		(0.24)
_Ibenarea_6		6.311		5.070		5.255
		(1.27)		(1.04)		(1.15)
_Ibenarea_7		12.572		11.534		11.688
		(2.16)*		(2.03)*		(2.30)*
_Ibenarea_8		5.534		4.745		5.880
		(1.26)		(1.10)		(1.45)
_Ibenarea_9		0.048		-1.528		-0.658
		(0.01)		(0.32)		(0.15)
anyeducr			-7.207	-7.279	-6.182	-6.189
			(2.28)*	(2.31)*	(2.14)*	(2.15)*
anyillr			0.010	0.018	-3.688	-3.617
			(0.01)	(0.01)	(2.10)*	(2.07)*
anyothr			-2.166	-2.087	-3.366	-3.293
			(0.84)	(0.81)	(1.36)	(1.34)
anysickr			10.867	10.754	6.540	6.375
			(5.28)**	(5.23)**	(3.31)**	(3.21)**
anytrair			-3.109	-3.291	-2.430	-2.609
			(0.84)	(0.88)	(0.67)	(0.71)
dssdate			-0.057	-0.056	-0.050	-0.047
			(2.25)*	(2.12)*	(2.15)*	(2.02)*
np100139			-3.809	-3.964	-4.976	-4.974
			(1.84)	(1.93)	(2.60)**	(2.61)**
np140189			-5.609	-5.709	-5.325	-5.335
			(2.66)**	(2.71)**	(2.74)**	(2.75)**
np190249			-5.928	-6.113	-5.202	-5.385
			(2.49)*	(2.56)*	(2.35)*	(2.43)*

Continued

Table A.4 Continued

	(1) pcben1	(2) pcben2	(3) pcben3	(4) Pcben4	(5) pcben5	(6) pcben6
np250p			-6.866	-7.157	-5.577	-5.842
			(3.03)**	(3.15)**	(2.66)**	(2.78)**
npdk			-3.818	-3.945	-4.225	-4.244
			(1.54)	(1.60)	(1.84)	(1.86)
skillman			-1.024	-1.096	0.633	0.613
			(0.47)	(0.50)	(0.31)	(0.30)
skillnm			0.840	0.627	2.173	1.991
			(0.35)	(0.26)	(0.98)	(0.90)
partskil			-0.227	-0.300	1.158	1.002
			(0.10)	(0.14)	(0.56)	(0.48)
unskill			-3.775	-3.778	-1.689	-1.660
			(1.38)	(1.38)	(0.66)	(0.64)
nojarmed			4.391	4.036	6.272	5.817
			(1.52)	(1.39)	(2.32)*	(2.15)*
nodkid			0.912	0.753	-1.062	-1.173
			(0.47)	(0.39)	(0.59)	(0.65)
twodkid			-4.571	-4.775	-4.515	-4.679
			(1.80)	(1.89)	(1.95)	(2.02)*
thrpdkid			-2.311	-2.314	-2.151	-2.039
			(0.82)	(0.82)	(0.81)	(0.77)
married			-7.418	-7.480	-4.394	-4.561
			(3.80)**	(3.83)**	(2.25)*	(2.33)*
cohab			-7.460	-7.409	-6.295	-6.328
			(2.92)**	(2.88)**	(2.62)**	(2.61)**
divorced			-3.427	-3.382	-3.986	-3.913
			(1.69)	(1.66)	(2.07)*	(2.03)*
separ			1.261	1.297	1.265	1.459
			(0.54)	(0.55)	(0.58)	(0.67)
widowed			-0.350	-0.544	1.443	1.273
			(0.09)	(0.14)	(0.39)	(0.35)
carenaff					-9.095	-9.044
					(4.05)**	(4.04)**
nocare					-5.245	-5.262
					(2.69)**	(2.70)**
ghfair					-9.133	-9.223
					(6.34)**	(6.39)**
ghgood					-16.810	-16.888
					(8.82)**	(8.78)**
hhwker1					-6.096	-5.998
					(4.22)**	(4.15)**
hhwker2p					-9.652	-9.713
					(4.47)**	(4.51)**
licandv					-5.236	-5.341
					(3.91)**	(3.95)**
licnoveh					2.659	2.276
					(1.55)	(1.32)
lsiaff					12.330	12.326
					(7.67)**	(7.65)**
lsidk					4.146	4.513
					(0.40)	(0.44)

Continued

Table A.4 Continued

	(1) pcben1	(2) pcben2	(3) pcben3	(4) Pcben4	(5) pcben5	(6) pcben6
lsinoaff					6.709	6.902
					(3.35)**	(3.43)**
mentdis					6.138	6.224
					(4.93)**	(4.99)**
phoner					-0.616	-0.696
					(0.41)	(0.47)
wafneg					-2.451	-2.543
					(1.49)	(1.55)
wafpos					-4.484	-4.564
					(2.94)**	(2.99)**
wamid					-0.544	-0.578
					(0.33)	(0.35)
wavpos					-2.585	-2.746
					(1.54)	(1.63)
Constant	50.337	53.598	907.331	891.911	799.439	767.891
	(11.01)**	(8.24)**	(2.40)*	(2.28)*	(2.35)*	(2.23)*
Observations	3242	3242	3242	3242	3242	3242
R-squared	0.21	0.21	0.23	0.24	0.34	0.34

Appendix B
Models for lone parents

Table B.1 Guide to meaning of variable names used in the analyses for lone parents

The list of variables and abbreviations used in the models for female lone parents (the reference categories are in bold).

Variable	Abbreviation
Age of respondent:	
- 18-19	**age1819**
- 20-24	age2024
- 25-29	age259
- 30-34	age304
- 35-39	age359
- 40-44	age405
- 45-49	age459
- 50 and more	ageove50
Marital status:	
- single	**single**
- married	married
- cohabiting	**cohab**
- widowed	widowed
- divorced	divorced
- separated	separ
Highest academic qualification obtained:	
- None or no information	**noqual**
- degree or equivalent	degree
- above A level-below degree	abovea
- A level or equivalent	alev
- GCSE A-C level or equivalent	gcseac
- GCSE D-E level or equivalnt	gcsede
- Foreign or other	foreign
Vocational education*	voceduc

Continued

Table B.1 Continued

Variable	Abbreviation
Number of dependent children:	
- one	**onekid**
- none	**nokid**
- two	twokid
- three	threekid
- four or more	fourkid
Ethnicity – white*	white
Age of youngest dependent child:	
- under 3 years old	**yngu3**
- 3 or 4 y.o.	yng34
- aged 5-10	yng510
- aged 11-15	yng1115
- aged 16-18	yng1618
Possesses telephone*	phoner
Licence and car access:	
- has no licence	**nolic**
- has licence but no car access	**licnoveh**
- has both	licandv
Long-standing illness disability:	
- does not have	**lsino**
- yes but has no affect on ability to work	lsinoaff
- yes and affects ability to work	lsiaff
Mental disability*	mentdis
General health perceived:	
- good	**ghgood**
- fair	**ghfair**
- not good	ghnotg
Numeracy problems*	num
Literacy problems*	litr
Housing tenure:	
- owner-occupation	**ownocc**
- LA sector	rentla
- HA sector	rentha
- PRS	rentpriv
- other	**tenoth**
Ever worked before*	evwkber
Any time in last 2 years spent*:	
- unemployed	anyunemr
- temporary sick/disabled**	anyillr
- long-term sick/disabled**	anysickr
- temporary or long-term sick/disabled**	anysikil
- in training	anytrair
- in education	anyeducr
- in other activity	anyothr
Number of workers in household excluding respondent:	
- none	**hhwker0**
- one	hhwker1
- two or more	hhwker2p

Continued

Table B.1 Continued

Variable	Abbreviation
Social class in last job before entry date:	
- **professional or intermediate**	**profint**
- skilled non-manual worker	skillnm
- skilled manual worker	skillman
- partly skilled manual	partskil
- unskilled manual	unskill
- no job or Armed Forces	nojarmed
Proportion of time working 1-15 hrs per week in 2 years pre ONE:	
- **no time**	**pr150**
- up to half time	pr15150
- over half time	pr1550p
Proportion of time working 16+ hrs per week in 2 years pre ONE:	
- **no time**	pr160
- up to 33% time	pr16133
- 34%-66% time	pr163466
- 67% to 99% time	pr166799
- all of time	pr16100
- No information	pr16dk
In receipt of benefits in 2 yr pre-ONE:	
- **none**	**nobben**
- out of work benefits only	oowbben
- in work benefits only	inwbben
- both oow and in work benefits	bothbben
Net pay per week in pre-ONE job:	
- **<£60 pw**	**npu60lp**
- £60-£84 pw	np6084lp
- £85-119 pw	np119lp
- £120-159 pw	np159lp
- £160+ pw	np160plp
- no job or no information	npdklp
24 benefit/model type areas	
- **benefit area 1**	**_Ibenarea_1**
- benefit areas 2-24	_ibenarea_
6 benefit/model type area	
- **Basic/ONE**	**basicone**
- Basic/Control	basiccon
- Call Centre/ONE	callone
- Call Centre/Control	callcon
- PVS/ONE	pvsone
- PVS/Control	pvscon
Care responsibilities	
- **no responsibility or no information**	**nocare**
- yes but doesn't affect work	carenaff
- yes and affects work	careaff
Who lives with:	
- **partner and/or children**	**livparch**
- parents	livparen
- others	livother
- alone	livalone

Continued

Table B.1 Continued

Variable	Abbreviation
TTWA characteristics	
The unemployment rate in 1999	uerate99
The change in the unemployment rate (comparing the rate in January to March 1999 with the rate in January to March 2000)	uechange
The total number of claimants of Incapacity Benefit, Disability Living Allowance, Severe Disablement Allowance, and Income Support claimed with a Disability Premium expressed as a proportion of the total workforce	disabpc
The change in the disability total as a percentage of the workforce, comparing February 2000 and May 2000	chansick
Lone parents claiming Income Support (without a Disability Premium) as a proportion of the total workforce	lonepc
The change in this proportion between February 2000 and May 2000	chanlp
Receives regular income other than earnings/benefits:*	
- child support	chsupp
- other	othincm
- private pension	privpen
Attitude towards work	
- very negative	wavneglp
- fairly negative	wafneglp
- middling	wamidlp
- fairly positive	wafposlp
- very positive	wavposlp

* These dummy variables are equal to 1 if true and 0 otherwise.
**Variable anysikil is used when we construct models predicting employment outcomes; variables anysickr and anyillr are used when we construct models predicting benefit outcomes.

Table B.2 Logit estimates for out-of-work status twelve months after their claim for benefit, lone mothers

	(1)	(2)	(3)	(4)	(5)	(6)
degree	-1.319	-1.382	-1.214	-1.231	-1.083	-1.091
	(5.55)**	(5.76)**	(4.42)**	(4.43)**	(3.78)**	(3.79)**
abovea	-0.507	-0.513	-0.316	-0.309	-0.209	-0.194
	(2.59)**	(2.62)**	(1.29)	(1.25)	(0.81)	(0.75)
alev	-0.679	-0.706	-0.491	-0.498	-0.461	-0.455
	(3.87)**	(4.00)**	(2.20)*	(2.21)*	(1.94)	(1.90)
gcseac	-0.408	-0.396	-0.209	-0.196	-0.180	-0.164
	(2.72)**	(2.60)**	(1.18)	(1.09)	(0.97)	(0.88)
gcsede	-0.322	-0.307	-0.146	-0.131	-0.139	-0.120
	(1.77)	(1.66)	(0.74)	(0.66)	(0.66)	(0.56)
foreign	-0.130	-0.182	-0.139	-0.154	-0.043	-0.048
	(0.52)	(0.72)	(0.54)	(0.59)	(0.16)	(0.18)
married	-0.476	-0.448	-0.586	-0.526	-0.371	-0.312
	(1.91)	(1.78)	(2.31)*	(2.03)*	(1.31)	(1.08)
cohab	-0.283	-0.248	-0.253	-0.228	-0.024	-0.005
	(1.02)	(0.89)	(0.89)	(0.81)	(0.07)	(0.02)
widowed	0.837	0.905	0.766	0.810	0.877	0.926
	(1.83)	(1.89)	(1.64)	(1.66)	(1.78)	(1.84)
divorced	-0.070	-0.088	-0.100	-0.127	-0.052	-0.077
	(0.48)	(0.60)	(0.65)	(0.82)	(0.32)	(0.48)
separ	-0.211	-0.244	-0.310	-0.324	-0.303	-0.314
	(1.51)	(1.72)	(2.08)*	(2.14)*	(1.96)	(1.99)*

Continued

Table B.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
nokid	-0.254	-0.255	-0.268	-0.285	-0.198	-0.179
	(0.92)	(0.93)	(0.90)	(0.95)	(0.40)	(0.35)
twokid	0.148	0.166	0.163	0.186	0.150	0.169
	(1.19)	(1.31)	(1.26)	(1.42)	(1.12)	(1.25)
threekid	0.284	0.249	0.315	0.303	0.239	0.231
	(1.61)	(1.38)	(1.67)	(1.57)	(1.21)	(1.15)
fourkid	0.321	0.319	0.351	0.364	0.153	0.155
	(1.36)	(1.36)	(1.42)	(1.47)	(0.57)	(0.58)
rentla	0.505	0.549	0.601	0.643	0.437	0.481
	(3.46)**	(3.65)**	(3.85)**	(4.02)**	(2.64)**	(2.85)**
rentha	0.414	0.450	0.508	0.535	0.377	0.399
	(2.50)*	(2.63)**	(2.91)**	(2.98)**	(2.03)*	(2.11)*
rentpriv	0.663	0.696	0.727	0.765	0.661	0.691
	(3.81)**	(3.89)**	(3.97)**	(4.11)**	(3.47)**	(3.60)**
tenoth	0.273	0.293	0.363	0.391	0.458	0.473
	(1.20)	(1.26)	(1.57)	(1.65)	(1.65)	(1.68)
yng34	-0.300	-0.283	-0.290	-0.269	-0.231	-0.220
	(1.76)	(1.64)	(1.65)	(1.51)	(1.28)	(1.21)
yng510	-0.753	-0.755	-0.757	-0.751	-0.778	-0.779
	(5.64)**	(5.54)**	(4.69)**	(4.60)**	(4.72)**	(4.66)**
yng1115	-0.967	-1.008	-1.003	-1.020	-1.065	-1.086
	(5.48)**	(5.59)**	(4.57)**	(4.63)**	(4.73)**	(4.79)**
yng1618	-0.484	-0.472	-0.655	-0.661	-0.782	-0.783
	(1.12)	(1.05)	(1.44)	(1.43)	(1.80)	(1.75)
pr16133	-0.114	-0.084	0.081	0.112	0.161	0.192
	(0.61)	(0.45)	(0.40)	(0.55)	(0.75)	(0.89)
pr163466	-0.297	-0.254	-0.106	-0.052	-0.035	0.012
	(1.58)	(1.32)	(0.52)	(0.25)	(0.16)	(0.06)
pr166799	-0.772	-0.781	-0.654	-0.642	-0.553	-0.533
	(4.42)**	(4.43)**	(3.35)**	(3.26)**	(2.75)**	(2.60)**
pr16100	-0.847	-0.824	-0.655	-0.607	-0.586	-0.539
	(4.83)**	(4.60)**	(3.03)**	(2.77)**	(2.59)**	(2.34)*
pr16dk	-0.770	-0.766	-0.793	-0.765	-0.698	-0.686
	(3.98)**	(3.85)**	(3.84)**	(3.62)**	(3.22)**	(3.12)**
pr15150	-0.679	-0.707	-0.520	-0.554	-0.516	-0.548
	(3.31)**	(3.44)**	(2.29)*	(2.44)*	(2.17)*	(2.30)*
pr1550p	-1.657	-1.654	-1.409	-1.407	-1.401	-1.403
	(7.71)**	(7.58)**	(5.96)**	(5.86)**	(5.66)**	(5.56)**
evwkber	-0.807	-0.789	-0.066	-0.060	-0.533	-0.540
	(4.16)**	(4.02)**	(0.10)	(0.09)	(0.78)	(0.79)
anysikil	0.197	0.183	0.034	0.025	-0.272	-0.269
	(0.87)	(0.79)	(0.14)	(0.11)	(1.09)	(1.07)
anyunemr	-0.057	-0.050	-0.088	-0.100	-0.087	-0.094
	(0.35)	(0.30)	(0.51)	(0.58)	(0.49)	(0.52)
anytrair	-0.989	-1.012	-1.022	-1.065	-1.028	-1.076
	(2.69)**	(2.73)**	(2.59)**	(2.74)**	(2.64)**	(2.80)**
anyeducr	0.064	0.069	0.113	0.127	0.049	0.058
	(0.34)	(0.36)	(0.57)	(0.63)	(0.22)	(0.26)
anyothr	-0.378	-0.409	-0.418	-0.439	-0.341	-0.357
	(1.40)	(1.55)	(1.49)	(1.59)	(1.25)	(1.32)
basiccon	0.136		0.229		0.189	
	(0.77)		(1.21)		(0.95)	

Continued

Table B.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
callone	-0.169		-0.069		-0.058	
	(0.96)		(0.36)		(0.29)	
callcon	-0.035		0.059		0.091	
	(0.20)		(0.31)		(0.46)	
pvsone	-0.111		0.023		0.006	
	(0.65)		(0.12)		(0.03)	
pvscon	0.278		0.370		0.367	
	(1.50)		(1.76)		(1.68)	
_Ibenarea_2		0.036		0.130		0.027
		(0.10)		(0.31)		(0.06)
_Ibenarea_3		0.253		0.378		0.415
		(0.76)		(0.70)		(0.74)
_Ibenarea_4		1.054		0.908		0.714
		(2.94)**		(2.35)*		(1.79)
_Ibenarea_5		0.022		0.139		0.088
		(0.06)		(0.34)		(0.21)
_Ibenarea_6		0.054		0.131		0.058
		(0.16)		(0.33)		(0.14)
_Ibenarea_7		0.082		0.179		0.134
		(0.23)		(0.37)		(0.26)
_Ibenarea_8		0.471		0.471		0.434
		(1.42)		(1.23)		(1.08)
_Ibenarea_9		0.172		0.242		0.148
		(0.55)		(0.64)		(0.37)
_Ibenarea_10		0.093		0.155		0.182
		(0.26)		(0.30)		(0.35)
_Ibenarea_11		0.085		0.145		0.085
		(0.28)		(0.41)		(0.23)
_Ibenarea_12		0.637		0.740		0.654
		(1.86)		(1.57)		(1.34)
_Ibenarea_13		0.844		0.835		0.765
		(2.67)**		(2.48)*		(2.14)*
_Ibenarea_14		0.329		0.437		0.376
		(0.89)		(1.03)		(0.85)
_Ibenarea_15		0.158		0.206		0.139
		(0.46)		(0.46)		(0.29)
_Ibenarea_16		0.393		0.493		0.284
		(1.08)		(1.18)		(0.66)
_Ibenarea_17		0.252		0.398		0.448
		(0.77)		(1.01)		(1.08)
_Ibenarea_18		0.279		0.287		0.185
		(0.84)		(0.77)		(0.48)
_Ibenarea_19		-0.024		0.052		0.042
		(0.08)		(0.13)		(0.10)
_Ibenarea_20		0.708		0.682		0.604
		(2.17)*		(1.68)		(1.42)
_Ibenarea_21		0.626		0.746		0.732
		(1.77)		(1.80)		(1.73)
_Ibenarea_22		1.113		1.332		1.197
		(2.83)**		(2.51)*		(2.16)*
_Ibenarea_23		0.482		0.472		0.295
		(1.39)		(1.02)		(0.61)
_Ibenarea_24		0.364		0.315		0.381
		(1.04)		(0.77)		(0.90)

Continued

Table B.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
age2024			-0.080	-0.114	-0.013	-0.023
			(0.23)	(0.32)	(0.04)	(0.06)
age259			0.181	0.145	0.289	0.274
			(0.51)	(0.40)	(0.78)	(0.74)
age304			0.094	0.037	0.264	0.231
			(0.25)	(0.10)	(0.68)	(0.60)
age359			0.251	0.205	0.439	0.418
			(0.65)	(0.53)	(1.10)	(1.04)
age405			0.087	0.044	0.110	0.090
			(0.22)	(0.11)	(0.26)	(0.21)
age459			0.278	0.263	0.260	0.257
			(0.60)	(0.56)	(0.52)	(0.51)
ageove50			1.052	0.978	0.904	0.841
			(1.90)	(1.74)	(1.53)	(1.38)
white			-0.242	-0.094	-0.102	0.022
			(1.08)	(0.40)	(0.42)	(0.09)
num			0.316	0.312	0.235	0.225
			(1.43)	(1.40)	(1.04)	(0.99)
litr			0.494	0.476	0.370	0.356
			(1.83)	(1.75)	(1.29)	(1.22)
voceduc			-0.123	-0.122	-0.126	-0.135
			(0.88)	(0.86)	(0.87)	(0.92)
oowbben			0.269	0.310	0.188	0.223
			(1.80)	(2.06)*	(1.22)	(1.45)
inwbben			-0.214	-0.204	-0.203	-0.198
			(1.30)	(1.22)	(1.19)	(1.15)
bothbben			-0.201	-0.155	-0.295	-0.252
			(1.07)	(0.81)	(1.50)	(1.25)
disabpc			-0.007	-0.015	-0.012	-0.022
			(0.35)	(0.36)	(0.58)	(0.52)
chansick			0.220	0.043	0.153	-0.001
			(0.71)	(0.12)	(0.47)	(0.00)
lonepc			0.074	0.036	0.097	0.071
			(0.58)	(0.23)	(0.70)	(0.42)
chanlp			0.002	0.106	0.045	0.244
			(0.00)	(0.19)	(0.08)	(0.40)
uerate99			0.013	0.043	-0.003	0.025
			(0.26)	(0.54)	(0.06)	(0.30)
uechange			-0.193	0.035	-0.246	-0.047
			(0.76)	(0.11)	(0.90)	(0.14)
np6084lp			0.142	0.120	0.107	0.084
			(0.84)	(0.71)	(0.61)	(0.47)
np119lp			0.029	0.019	-0.025	-0.036
			(0.16)	(0.10)	(0.13)	(0.18)
np159lp			0.326	0.285	0.331	0.294
			(1.67)	(1.45)	(1.66)	(1.46)
np160plp			0.215	0.177	0.117	0.084
			(1.03)	(0.84)	(0.54)	(0.39)
npdklp			0.289	0.305	0.187	0.195
			(1.03)	(1.09)	(0.61)	(0.65)
skillnm			-0.060	-0.062	-0.076	-0.074
			(0.31)	(0.31)	(0.37)	(0.35)

Continued

Table B.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
skillman			-0.079	-0.072	-0.156	-0.140
			(0.33)	(0.29)	(0.62)	(0.55)
partskil			0.075	0.091	0.020	0.043
			(0.38)	(0.46)	(0.09)	(0.21)
unskill			-0.139	-0.133	-0.246	-0.231
			(0.58)	(0.54)	(0.95)	(0.88)
nojarmed			0.388	0.386	-0.120	-0.118
			(0.61)	(0.61)	(0.19)	(0.19)
carenaff					-0.037	-0.058
					(0.26)	(0.41)
careaff					0.307	0.322
					(1.42)	(1.49)
chsupp					0.026	0.030
					(0.17)	(0.20)
privpen					0.565	0.703
					(0.59)	(0.72)
othincm					1.088	1.103
					(2.98)**	(2.96)**
hhwker1					-0.503	-0.487
					(2.35)*	(2.24)*
hhwker2p					-0.218	-0.196
					(0.61)	(0.56)
livparen					-0.326	-0.248
					(0.25)	(0.19)
livother					1.050	0.956
					(0.81)	(0.73)
livalone					-0.331	-0.392
					(0.58)	(0.67)
ghfair					0.019	0.015
					(0.14)	(0.11)
ghnotg					0.269	0.292
					(1.41)	(1.54)
lsinoaff					-0.254	-0.236
					(1.35)	(1.26)
lsiaff					0.608	0.588
					(2.81)**	(2.72)**
mentdis					0.006	-0.012
					(0.02)	(0.05)
phoner					-0.727	-0.737
					(2.63)**	(2.69)**
licnoveh					-0.012	-0.026
					(0.07)	(0.14)
licandv					-0.458	-0.450
					(3.63)**	(3.50)**
wafneglp					-0.035	-0.051
					(0.19)	(0.27)
wamidlp					-0.371	-0.370
					(1.93)	(1.90)
wafposlp					-0.624	-0.650
					(3.56)**	(3.67)**
wavposlp					-0.921	-0.924
					(5.05)**	(5.04)**
Constant	2.543	2.161	1.157	0.842	2.761	2.514
	(8.71)**	(6.16)**	(1.25)	(0.85)	(2.78)**	(2.38)*
Observations	2333	2333	2333	2333	2333	2333

Table B.3 Logit estimates for out-of-work benefit receipt twelve months after their claim for benefit, lone mothers

	(1)	(2)	(3)	(4)	(5)	(6)
degree	-0.626	-0.713	-0.437	-0.459	-0.464	-0.466
	(2.86)**	(3.19)**	(1.71)	(1.77)	(1.73)	(1.70)
abovea	-0.728	-0.732	-0.495	-0.484	-0.414	-0.425
	(3.91)**	(3.93)**	(2.11)*	(2.04)*	(1.67)	(1.69)
alev	-0.758	-0.809	-0.548	-0.588	-0.509	-0.552
	(4.59)**	(4.78)**	(2.61)**	(2.75)**	(2.32)*	(2.47)*
gcseac	-0.318	-0.313	-0.107	-0.112	-0.066	-0.074
	(2.23)*	(2.16)*	(0.63)	(0.65)	(0.37)	(0.41)
gcsede	-0.414	-0.430	-0.273	-0.287	-0.233	-0.251
	(2.31)*	(2.34)*	(1.42)	(1.46)	(1.15)	(1.21)
foreign	-0.276	-0.354	-0.245	-0.288	-0.178	-0.216
	(1.16)	(1.46)	(0.97)	(1.13)	(0.69)	(0.83)
married	-1.372	-1.402	-1.545	-1.537	-1.082	-1.068
	(5.65)**	(5.69)**	(6.15)**	(6.04)**	(3.84)**	(3.68)**
cohab	-1.202	-1.200	-1.253	-1.248	-0.949	-0.956
	(4.71)**	(4.52)**	(4.85)**	(4.73)**	(3.00)**	(3.01)**
widowed	1.328	1.363	1.142	1.207	1.215	1.295
	(2.41)*	(2.35)*	(2.02)*	(2.03)*	(2.04)*	(2.14)*
divorced	-0.066	-0.072	-0.122	-0.147	-0.115	-0.147
	(0.47)	(0.50)	(0.80)	(0.95)	(0.72)	(0.89)
separ	-0.084	-0.113	-0.192	-0.209	-0.242	-0.260
	(0.62)	(0.82)	(1.34)	(1.41)	(1.58)	(1.64)
nokid	-0.622	-0.588	-0.639	-0.631	-0.600	-0.555
	(2.64)**	(2.47)*	(2.55)*	(2.47)*	(1.38)	(1.26)
twokid	-0.104	-0.106	-0.082	-0.081	-0.155	-0.151
	(0.86)	(0.87)	(0.65)	(0.64)	(1.17)	(1.13)
threekid	0.177	0.182	0.203	0.224	0.043	0.074
	(1.07)	(1.07)	(1.16)	(1.25)	(0.24)	(0.39)
fourkid	0.321	0.299	0.312	0.310	0.073	0.065
	(1.38)	(1.30)	(1.30)	(1.30)	(0.29)	(0.25)
rentla	0.538	0.544	0.665	0.656	0.404	0.390
	(3.74)**	(3.71)**	(4.31)**	(4.19)**	(2.47)*	(2.35)*
rentha	0.579	0.636	0.711	0.745	0.464	0.491
	(3.52)**	(3.78)**	(4.14)**	(4.22)**	(2.56)*	(2.64)**
rentpriv	0.552	0.578	0.650	0.680	0.420	0.450
	(3.35)**	(3.43)**	(3.77)**	(3.87)**	(2.33)*	(2.45)*
tenoth	0.482	0.496	0.565	0.569	0.708	0.695
	(2.12)*	(2.14)*	(2.45)*	(2.43)*	(2.37)*	(2.29)*
yng34	-0.579	-0.547	-0.566	-0.549	-0.487	-0.473
	(3.77)**	(3.51)**	(3.61)**	(3.42)**	(2.93)**	(2.79)**
yng510	-0.529	-0.533	-0.517	-0.525	-0.550	-0.552
	(4.18)**	(4.12)**	(3.58)**	(3.55)**	(3.70)**	(3.60)**
yng1115	-0.643	-0.703	-0.712	-0.754	-0.858	-0.910
	(3.64)**	(3.88)**	(3.47)**	(3.59)**	(3.98)**	(4.14)**
yng1618	-0.429	-0.435	-0.538	-0.564	-0.898	-0.920
	(0.93)	(0.95)	(1.06)	(1.11)	(1.87)	(1.92)
pr16133	0.086	0.070	0.197	0.184	0.273	0.258
	(0.49)	(0.39)	(1.00)	(0.92)	(1.33)	(1.25)
pr163466	-0.280	-0.245	-0.118	-0.070	0.004	0.051
	(1.57)	(1.35)	(0.60)	(0.35)	(0.02)	(0.23)

Continued

Table B.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
pr166799	-0.586	-0.636	-0.498	-0.538	-0.346	-0.387
	(3.35)**	(3.53)**	(2.55)*	(2.72)**	(1.73)	(1.88)
pr16100	-0.569	-0.565	-0.440	-0.440	-0.335	-0.352
	(3.27)**	(3.15)**	(2.06)*	(2.01)*	(1.44)	(1.49)
pr16dk	-0.747	-0.742	-0.808	-0.799	-0.748	-0.762
	(3.95)**	(3.86)**	(4.12)**	(3.97)**	(3.52)**	(3.52)**
pr15150	-0.117	-0.134	-0.193	-0.230	-0.260	-0.298
	(0.54)	(0.62)	(0.84)	(0.99)	(1.06)	(1.21)
pr1550p	-0.344	-0.265	-0.348	-0.318	-0.245	-0.223
	(1.54)	(1.18)	(1.38)	(1.26)	(0.90)	(0.82)
evwkber	-0.552	-0.488	0.751	0.631	0.531	0.429
	(3.39)**	(2.97)**	(1.01)	(0.89)	(0.70)	(0.60)
anyillr	0.256	0.234	0.151	0.142	-0.294	-0.308
	(0.95)	(0.85)	(0.53)	(0.50)	(1.00)	(1.03)
anyunemr	0.051	0.090	0.099	0.109	0.010	0.027
	(0.33)	(0.57)	(0.58)	(0.64)	(0.06)	(0.15)
anysickr	2.421	2.357	2.199	2.122	1.471	1.355
	(2.15)*	(2.11)*	(1.95)	(1.86)	(1.34)	(1.22)
anytrair	-1.013	-0.988	-1.104	-1.107	-1.112	-1.119
	(2.64)**	(2.51)*	(2.77)**	(2.71)**	(2.72)**	(2.65)**
anyeducr	-1.355	-1.397	-1.438	-1.500	-1.077	-1.146
	(7.96)**	(7.93)**	(7.70)**	(7.82)**	(5.30)**	(5.52)**
anyothr	-0.120	-0.147	-0.179	-0.193	-0.042	-0.058
	(0.51)	(0.63)	(0.73)	(0.78)	(0.18)	(0.24)
basiccon	0.046		0.178		0.162	
	(0.26)		(0.96)		(0.83)	
callone	-0.145		0.023		0.129	
	(0.82)		(0.12)		(0.64)	
callcon	-0.197		-0.058		0.040	
	(1.16)		(0.31)		(0.19)	
pvsone	-0.111		0.124		0.142	
	(0.66)		(0.67)		(0.73)	
pvscon	0.119		0.289		0.366	
	(0.68)		(1.45)		(1.75)	
_Ibenarea_2		-0.254		-0.065		-0.211
		(0.67)		(0.15)		(0.47)
_Ibenarea_3		-0.048		-0.017		0.137
		(0.14)		(0.03)		(0.25)
_Ibenarea_4		0.987		0.984		0.709
		(2.90)**		(2.65)**		(1.79)
_Ibenarea_5		-0.404		-0.114		-0.085
		(1.16)		(0.28)		(0.19)
_Ibenarea_6		0.386		0.776		0.818
		(1.11)		(1.99)*		(1.93)
_Ibenarea_7		-0.120		-0.140		-0.033
		(0.35)		(0.29)		(0.06)
_Ibenarea_8		0.210		0.340		0.357
		(0.63)		(0.91)		(0.90)
_Ibenarea_9		-0.092		0.155		0.063
		(0.29)		(0.42)		(0.16)
_Ibenarea_10		-0.261		0.013		-0.005
		(0.76)		(0.03)		(0.01)

Continued

Table B.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
_Ibenarea_11		0.285		0.532		0.528
		(0.93)		(1.53)		(1.47)
_Ibenarea_12		0.314		0.498		0.552
		(0.94)		(1.11)		(1.16)
_Ibenarea_13		0.584		0.746		0.601
		(1.83)		(2.21)*		(1.69)
_Ibenarea_14		-0.006		0.269		0.240
		(0.02)		(0.65)		(0.55)
_Ibenarea_15		-0.046		0.241		0.176
		(0.14)		(0.56)		(0.36)
_Ibenarea_16		0.269		0.396		0.300
		(0.76)		(0.99)		(0.71)
_Ibenarea_17		0.041		0.464		0.546
		(0.13)		(1.22)		(1.37)
_Ibenarea_18		-0.330		0.000		-0.055
		(1.00)		(0.00)		(0.15)
_Ibenarea_19		0.117		0.397		0.444
		(0.35)		(1.02)		(1.05)
_Ibenarea_20		0.166		-0.070		-0.124
		(0.53)		(0.18)		(0.30)
_Ibenarea_21		0.059		0.261		0.278
		(0.19)		(0.69)		(0.71)
_Ibenarea_22		1.335		1.544		1.763
		(3.51)**		(3.06)**		(3.34)**
_Ibenarea_23		0.076		0.009		-0.005
		(0.23)		(0.02)		(0.01)
_Ibenarea_24		0.183		0.170		0.167
		(0.53)		(0.43)		(0.41)
age2024			-0.616	-0.710	-0.416	-0.508
			(1.74)	(1.97)*	(1.16)	(1.41)
age259			-0.418	-0.488	-0.108	-0.179
			(1.16)	(1.33)	(0.29)	(0.48)
age304			-0.407	-0.485	-0.056	-0.147
			(1.10)	(1.30)	(0.15)	(0.39)
age359			-0.320	-0.380	0.083	0.023
			(0.84)	(0.98)	(0.21)	(0.06)
age405			-0.343	-0.464	0.060	-0.078
			(0.85)	(1.13)	(0.14)	(0.19)
age459			-0.237	-0.339	0.127	0.021
			(0.52)	(0.73)	(0.27)	(0.04)
ageove50			0.412	0.328	0.788	0.714
			(0.73)	(0.57)	(1.27)	(1.16)
white			-0.270	-0.073	-0.055	0.107
			(1.37)	(0.35)	(0.26)	(0.48)
num			0.245	0.235	0.194	0.189
			(1.16)	(1.08)	(0.87)	(0.83)
litr			0.406	0.423	0.349	0.365
			(1.64)	(1.68)	(1.30)	(1.33)
voceduc			-0.071	-0.072	-0.063	-0.065
			(0.53)	(0.53)	(0.45)	(0.45)
oowbben			0.061	0.077	0.054	0.062
			(0.44)	(0.55)	(0.37)	(0.41)

Continued

Table B.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
inwbben			-0.169	-0.156	-0.170	-0.168
			(1.04)	(0.94)	(1.00)	(0.97)
bothbben			-0.185	-0.175	-0.227	-0.222
			(0.98)	(0.91)	(1.16)	(1.10)
disabpc			-0.017	0.002	-0.028	-0.026
			(0.88)	(0.06)	(1.43)	(0.64)
chansick			0.484	0.280	0.493	0.283
			(1.64)	(0.83)	(1.57)	(0.79)
lonepc			0.159	0.083	0.204	0.146
			(1.33)	(0.55)	(1.57)	(0.90)
chanlp			-0.112	0.138	-0.003	0.399
			(0.22)	(0.25)	(0.01)	(0.70)
uerate99			-0.016	0.017	-0.038	0.012
			(0.32)	(0.22)	(0.77)	(0.14)
uechange			-0.336	-0.493	-0.328	-0.474
			(1.37)	(1.63)	(1.29)	(1.52)
np6084lp			-0.212	-0.260	-0.277	-0.326
			(1.26)	(1.53)	(1.55)	(1.83)
np119lp			-0.299	-0.354	-0.322	-0.380
			(1.61)	(1.88)	(1.63)	(1.90)
np159lp			-0.294	-0.380	-0.317	-0.396
			(1.47)	(1.89)	(1.52)	(1.87)
np160plp			-0.074	-0.128	-0.074	-0.117
			(0.36)	(0.61)	(0.34)	(0.54)
npdklp			-0.091	-0.146	-0.235	-0.292
			(0.32)	(0.50)	(0.80)	(0.97)
skillnm			0.124	0.095	0.108	0.075
			(0.66)	(0.50)	(0.53)	(0.37)
skillman			0.092	0.065	-0.049	-0.064
			(0.40)	(0.27)	(0.20)	(0.25)
partskil			0.272	0.288	0.169	0.185
			(1.43)	(1.50)	(0.81)	(0.88)
unskill			0.007	-0.008	-0.094	-0.112
			(0.03)	(0.03)	(0.36)	(0.43)
nojarmed			1.253	1.108	0.971	0.844
			(1.78)	(1.66)	(1.33)	(1.25)
carenaff					0.013	0.019
					(0.09)	(0.13)
careaff					0.464	0.521
					(2.12)*	(2.32)*
chsupp					-0.283	-0.285
					(1.85)	(1.85)
privpen					0.214	0.265
					(0.19)	(0.22)
othincm					-1.581	-1.630
					(4.94)**	(4.87)**
hhwker1					-1.246	-1.250
					(6.18)**	(6.10)**
hhwker2p					-0.389	-0.384
					(1.02)	(0.98)
livparen					-0.816	-0.611
					(0.60)	(0.48)

Continued

Table B.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
livother					-0.095	-0.092
					(0.11)	(0.11)
livalone					-0.252	-0.297
					(0.49)	(0.57)
ghfair					0.141	0.143
					(1.12)	(1.11)
ghnotg					0.394	0.428
					(2.13)*	(2.34)*
lsinoaff					-0.271	-0.242
					(1.44)	(1.27)
lsiaff					0.557	0.551
					(2.76)**	(2.72)**
mentdis					-0.043	-0.075
					(0.18)	(0.30)
phoner					-0.444	-0.493
					(1.62)	(1.78)
licnoveh					-0.111	-0.120
					(0.62)	(0.66)
licandv					-0.420	-0.401
					(3.38)**	(3.16)**
wafneglp					-0.021	-0.054
					(0.12)	(0.32)
wamidlp					-0.125	-0.113
					(0.69)	(0.62)
wafposlp					-0.101	-0.099
					(0.60)	(0.58)
wavposlp					-0.936	-0.933
					(5.34)**	(5.30)**
Constant	2.067	1.828	0.703	0.385	1.576	1.432
	(7.48)**	(5.28)**	(0.73)	(0.39)	(1.52)	(1.34)
Observations	2331	2331	2331	2331	2331	2331

Table B.4 OLS estimates of percentage of time lone mothers spend on out-of-work benefits, DSSDATE-31/12/02, OLS

	pcben1	pcben2	pcben3	pcben4	pcben5	pcben6
degree	-17.619	-18.372	-12.147	-12.412	-10.154	-10.162
	(6.45)**	(6.74)**	(3.93)**	(4.03)**	(3.43)**	(3.44)**
abovea	-8.058	-7.633	-3.521	-3.419	-2.914	-2.667
	(3.44)**	(3.29)**	(1.24)	(1.21)	(1.08)	(0.99)
alev	-10.000	-9.865	-6.051	-6.184	-5.377	-5.331
	(5.05)**	(4.96)**	(2.47)*	(2.52)*	(2.32)*	(2.29)*
gcseac	-6.073	-5.861	-2.581	-2.550	-1.818	-1.644
	(3.96)**	(3.81)**	(1.44)	(1.42)	(1.05)	(0.95)
gcsede	-5.916	-6.054	-4.178	-4.503	-3.701	-3.821
	(2.94)**	(3.00)**	(2.00)*	(2.16)*	(1.84)	(1.90)
foreign	-5.543	-5.706	-3.722	-3.911	-1.825	-1.783
	(1.97)*	(2.04)*	(1.28)	(1.35)	(0.67)	(0.66)
married	-31.983	-32.244	-32.316	-32.026	-28.299	-28.146
	(10.77)**	(10.89)**	(10.98)**	(10.86)**	(9.33)**	(9.29)**
cohab	-29.608	-29.906	-30.267	-30.380	-26.439	-26.745
	(9.67)**	(9.72)**	(9.96)**	(9.97)**	(8.23)**	(8.33)**
widowed	25.048	24.392	23.795	23.726	23.595	23.542
	(9.23)**	(8.74)**	(7.91)**	(7.61)**	(7.47)**	(7.27)**
divorced	-2.332	-2.750	-2.628	-2.909	-2.534	-2.777
	(1.40)	(1.64)	(1.49)	(1.65)	(1.49)	(1.64)
separ	0.004	-0.357	0.188	0.033	-0.685	-0.824
	(0.00)	(0.23)	(0.12)	(0.02)	(0.44)	(0.53)
nokid	-1.414	-0.331	-1.489	-0.846	-2.141	-1.598
	(0.51)	(0.12)	(0.50)	(0.29)	(0.73)	(0.55)
twokid	0.354	0.530	0.826	1.018	-0.218	-0.062
	(0.25)	(0.37)	(0.56)	(0.69)	(0.15)	(0.04)
threekid	0.644	0.911	1.360	1.738	-0.475	-0.078
	(0.33)	(0.47)	(0.68)	(0.87)	(0.25)	(0.04)
fourkid	2.488	2.474	3.000	3.136	-0.307	-0.110
	(1.02)	(1.01)	(1.18)	(1.24)	(0.12)	(0.04)
rentla	6.380	6.357	6.226	5.868	2.967	2.506
	(3.41)**	(3.36)**	(3.25)**	(3.04)**	(1.61)	(1.35)
rentha	7.074	7.174	7.233	6.857	3.909	3.570
	(3.36)**	(3.40)**	(3.39)**	(3.20)**	(1.90)	(1.73)
rentpriv	8.388	8.090	8.107	7.621	6.095	5.555
	(4.03)**	(3.87)**	(3.84)**	(3.59)**	(3.00)**	(2.73)**
tenoth	0.184	-0.433	-0.434	-1.032	-0.940	-1.767
	(0.07)	(0.16)	(0.16)	(0.38)	(0.31)	(0.59)
yng34	-7.300	-6.989	-6.751	-6.641	-6.273	-6.143
	(4.27)**	(4.10)**	(3.84)**	(3.79)**	(3.70)**	(3.64)**
yng0510	-7.692	-7.430	-7.335	-7.198	-8.442	-8.353
	(5.29)**	(5.10)**	(4.46)**	(4.39)**	(5.35)**	(5.30)**
yng1115	-9.847	-9.429	-9.603	-9.318	-11.613	-11.279
	(4.60)**	(4.40)**	(3.91)**	(3.80)**	(4.89)**	(4.76)**
yng1618	-0.546	0.660	-4.851	-3.992	-9.595	-8.845
	(0.12)	(0.15)	(0.94)	(0.77)	(2.02)*	(1.86)
pr16133	1.300	1.454	1.965	2.108	2.929	2.984
	(0.69)	(0.77)	(0.95)	(1.03)	(1.49)	(1.53)
pr163466	-2.017	-1.756	-0.647	-0.531	1.656	1.701
	(0.95)	(0.82)	(0.29)	(0.24)	(0.75)	(0.77)

Continued

Table B.4 Continued

	pcben1	pcben2	pcben3	pcben4	pcben5	pcben6
pr166799	-5.566	-5.588	-3.529	-3.206	-2.009	-1.772
	(2.56)*	(2.57)*	(1.50)	(1.36)	(0.90)	(0.79)
pr16100	-6.257	-5.865	-2.193	-1.678	-0.479	-0.054
	(2.99)**	(2.80)**	(0.88)	(0.67)	(0.20)	(0.02)
pr16dk	-11.471	-11.130	-11.318	-10.723	-9.508	-9.061
	(4.85)**	(4.70)**	(4.67)**	(4.39)**	(4.06)**	(3.87)**
pr15150	-0.503	-0.215	-1.863	-1.963	-1.024	-1.013
	(0.19)	(0.08)	(0.69)	(0.73)	(0.40)	(0.40)
pr1550p	-5.429	-5.039	-5.592	-5.535	-3.007	-2.909
	(1.89)	(1.77)	(1.88)	(1.87)	(1.09)	(1.06)
evwkber	-6.776	-6.385	-6.841	-7.647	-8.521	-9.281
	(4.22)**	(3.99)**	(1.14)	(1.28)	(1.60)	(1.75)
basiccon	-0.487		0.281		0.132	
	(0.24)		(0.14)		(0.07)	
callone	-1.501		-0.195		0.466	
	(0.75)		(0.09)		(0.23)	
callcon	-1.272		-1.143		-0.282	
	(0.65)		(0.56)		(0.14)	
pvsone	-3.535		-2.021		-1.842	
	(1.78)		(0.95)		(0.91)	
pvscon	2.813		3.963		4.955	
	(1.45)		(1.86)		(2.39)*	
anyillr	4.157	4.073	3.907	3.838	-0.571	-0.663
	(1.49)	(1.46)	(1.40)	(1.37)	(0.21)	(0.24)
anyunemr	-0.083	0.163	-0.425	-0.388	-0.197	-0.207
	(0.05)	(0.09)	(0.24)	(0.22)	(0.11)	(0.12)
anysickr	14.167	14.417	13.880	14.322	5.674	6.174
	(4.16)**	(4.26)**	(3.89)**	(4.00)**	(1.45)	(1.57)
anytrair	-9.925	-8.984	-9.594	-9.553	-10.430	-10.389
	(2.10)*	(1.90)	(1.95)	(1.97)*	(2.25)*	(2.28)*
anyeducr	-19.709	-18.846	-19.677	-19.249	-16.178	-15.929
	(9.14)**	(8.74)**	(8.89)**	(8.71)**	(7.17)**	(7.07)**
anyothr	-0.962	-1.164	-0.949	-1.256	-0.380	-0.673
	(0.32)	(0.39)	(0.32)	(0.43)	(0.13)	(0.24)
age2024			-6.444	-6.764	-4.971	-5.298
			(2.27)*	(2.39)*	(1.77)	(1.88)
age259			-6.581	-7.064	-4.521	-4.891
			(2.21)*	(2.37)*	(1.52)	(1.64)
age304			-6.252	-6.473	-4.107	-4.149
			(1.98)*	(2.06)*	(1.30)	(1.31)
age359			-5.533	-5.956	-2.746	-2.991
			(1.66)	(1.79)	(0.83)	(0.90)
age405			-5.199	-5.856	-3.084	-3.638
			(1.39)	(1.58)	(0.84)	(0.99)
age459			-7.508	-8.339	-5.487	-6.228
			(1.62)	(1.80)	(1.22)	(1.38)
ageove50			6.770	6.423	7.427	6.940
			(1.17)	(1.11)	(1.33)	(1.23)
white			-1.763	-0.057	0.867	2.469
			(0.82)	(0.03)	(0.42)	(1.13)
num			6.517	6.280	3.527	3.297
			(3.12)**	(2.98)**	(1.68)	(1.56)

Continued

Table B.4 Continued

	pcben1	pcben2	pcben3	pcben4	pcben5	pcben6
litr			0.530	0.550	-0.838	-0.725
			(0.23)	(0.24)	(0.36)	(0.31)
voceduc			-1.903	-1.654	-1.485	-1.272
			(1.19)	(1.04)	(0.97)	(0.84)
oowbben			2.754	2.812	2.080	2.159
			(1.83)	(1.88)	(1.41)	(1.47)
inwbben			-1.456	-1.340	-1.620	-1.554
			(0.72)	(0.67)	(0.86)	(0.83)
bothbben			1.981	2.191	0.374	0.514
			(0.94)	(1.05)	(0.19)	(0.26)
disabpc			-0.272	0.571	-0.448	0.374
			(1.27)	(1.29)	(2.17)*	(0.89)
chansick			8.359	6.262	6.774	4.856
			(2.49)*	(1.61)	(2.11)*	(1.29)
lonepc			1.086	-1.838	1.672	-1.147
			(0.80)	(1.07)	(1.27)	(0.69)
chanlp			-0.908	-3.815	-2.485	-4.705
			(0.17)	(0.64)	(0.50)	(0.82)
uerate99			-0.011	0.447	-0.298	-0.074
			(0.02)	(0.51)	(0.57)	(0.09)
uechange			-3.333	-6.477	-2.440	-5.862
			(1.18)	(1.86)	(0.90)	(1.75)
np6084lp			-4.585	-4.998	-4.341	-4.743
			(2.30)*	(2.53)*	(2.30)*	(2.53)*
np119lp			-4.027	-4.391	-3.970	-4.239
			(1.84)	(2.01)*	(1.92)	(2.05)*
np159lp			-3.866	-4.209	-3.181	-3.367
			(1.75)	(1.90)	(1.52)	(1.60)
np160plp			-6.581	-7.297	-6.502	-7.103
			(2.87)**	(3.18)**	(3.02)**	(3.27)**
npdklp			-3.623	-4.225	-4.602	-5.166
			(1.12)	(1.31)	(1.53)	(1.72)
skillnm			1.811	2.021	1.957	2.169
			(0.77)	(0.85)	(0.88)	(0.97)
skillman			1.738	2.009	0.938	1.155
			(0.61)	(0.71)	(0.35)	(0.43)
partskil			5.557	5.790	4.638	4.837
			(2.35)*	(2.44)*	(2.09)*	(2.17)*
unskill			2.583	2.986	1.841	2.114
			(0.88)	(1.02)	(0.66)	(0.76)
nojarmed			1.921	1.477	0.116	-0.398
			(0.33)	(0.25)	(0.02)	(0.08)
carenaff					2.170	2.248
					(1.46)	(1.52)
careaff					16.678	16.708
					(9.14)**	(9.17)**
chsupp					-5.055	-5.240
					(3.01)**	(3.15)**
privpen					3.129	3.098
					(0.46)	(0.44)
othincm					-3.956	-3.544
					(1.28)	(1.18)

Continued

Table B.4 Continued

	pcben1	pcben2	pcben3	pcben4	pcben5	pcben6
hhwker1					-11.081	-11.000
					(5.02)**	(4.98)**
hhwker2p					-1.601	-1.137
					(0.41)	(0.29)
ghfair					3.649	3.447
					(2.78)**	(2.63)**
ghnotg					8.839	8.907
					(4.87)**	(4.87)**
lsinoaff					-1.540	-1.409
					(0.74)	(0.68)
lsiaff					5.679	5.927
					(3.29)**	(3.41)**
mentdis					0.772	0.397
					(0.36)	(0.19)
phoner					-0.247	-0.564
					(0.14)	(0.32)
licnoveh					1.591	1.214
					(0.90)	(0.68)
licandv					-5.417	-5.648
					(4.03)**	(4.16)**
wafneglp					1.230	0.989
					(0.77)	(0.62)
wamidlp					-1.935	-2.157
					(1.14)	(1.27)
wafposlp					-0.796	-0.886
					(0.49)	(0.54)
wavposlp					-8.806	-8.841
					(4.66)**	(4.67)**
_Ibenarea_2		-5.610		-6.791		-7.713
		(1.37)		(1.45)		(1.71)
_Ibenarea_3		-5.852		-13.117		-13.298
		(1.37)		(2.10)*		(2.27)*
_Ibenarea_4		4.631		4.878		2.945
		(1.25)		(1.23)		(0.76)
_Ibenarea_5		-3.650		-4.973		-5.281
		(0.86)		(0.99)		(1.11)
_Ibenarea_6		-0.134		2.031		1.600
		(0.04)		(0.48)		(0.39)
_Ibenarea_7		-5.576		-9.689		-10.322
		(1.38)		(1.67)		(1.85)
_Ibenarea_8		-3.091		-4.359		-4.590
		(0.85)		(1.07)		(1.16)
_Ibenarea_9		-5.073		-6.063		-6.997
		(1.41)		(1.45)		(1.74)
_Ibenarea_10		-3.970		-5.346		-5.124
		(0.88)		(0.88)		(0.88)
_Ibenarea_11		-3.629		-4.372		-5.130
		(1.03)		(1.09)		(1.34)
_Ibenarea_12		-6.917		-11.360		-11.768
		(1.67)		(2.08)*		(2.25)*
_Ibenarea_13		2.328		3.187		1.226
		(0.65)		(0.84)		(0.33)

Continued

Table B.4 Continued

	pcben1	pcben2	pcben3	pcben4	pcben5	pcben6
_Ibenarea_14		-2.117		-1.563		-2.910
		(0.51)		(0.33)		(0.64)
_Ibenarea_15		-8.572		-9.204		-8.589
		(2.06)*		(1.82)		(1.75)
_Ibenarea_16		-1.549		-4.015		-4.968
		(0.41)		(0.92)		(1.21)
_Ibenarea_17		-5.515		-4.014		-3.966
		(1.46)		(0.90)		(0.92)
_Ibenarea_18		-5.303		-3.211		-5.099
		(1.43)		(0.78)		(1.30)
_Ibenarea_19		0.924		-0.674		-0.400
		(0.25)		(0.15)		(0.09)
_Ibenarea_20		-0.662		-6.316		-5.075
		(0.18)		(1.47)		(1.22)
_Ibenarea_21		-1.495		-2.636		-3.730
		(0.40)		(0.60)		(0.86)
_Ibenarea_22		4.609		0.707		1.078
		(1.29)		(0.14)		(0.22)
_Ibenarea_23		-0.202		-6.166		-6.213
		(0.05)		(1.22)		(1.29)
_Ibenarea_24		4.419		1.136		3.805
		(1.13)		(0.26)		(0.91)
Constant	85.674	86.260	86.952	86.973	88.706	90.970
	(29.70)**	(23.73)**	(10.57)**	(9.31)**	(11.20)**	(10.17)**
Observations	2979	2979	2979	2979	2979	2979
R-squared	0.20	0.21	0.22	0.23	0.29	0.30

Appendix C
Models for JSA clients

Table C.1 Guide to meaning of variable names used in the analyses for JSA clients

The list of variables and abbreviations used in the models for JSA clients (the reference categories are in bold).

Variable	Abbreviation
Gender – female*	fem
Age of respondent:	
- 17-19	**age1719**
- 20-24	age2024
- 25-29	age259
- 30-34	age304
- 35-39	age359
- 40-44	age405
- 45-49	age459
- 50-54	age5054
- 55-60	age5560
Ethnicity - white*	white
Marital status:	
- single	**single**
- married	married
- cohabiting	cohab
- widowed	widowed
- divorced	divorced
- separated	separ
Age of youngest dependent child:	
- under 3 years old	**yngu3**
- 3 or 4 y.o.	yng34
- aged 5-10	yng510
- aged 11-18	yng1118
- no children	yngnokid

Continued

Table C.1 Continued

Variable	Abbreviation
Highest academic qualification obtained:	
- **None or no information**	**noqual**
- degree or equivalent	degree
- above A level-below degree	abovea
- A level or equivalent	alev
- GCSE A-C level or equivalent	gcseac
- GCSE D-E level or equivalnt	gcsede
- Foreign or other	foreign
Numeracy problems*	num
Literacy problems*	litr
Housing tenure:	
- **owner-occupation**	**ownocc**
- LA sector	rentla
- HA sector	rentha
- PRS	rentpriv
- other	tenoth
- insitutions	tenin
In receipt of benefits in 2 yr pre-ONE:	
- **none**	**nobben**
- out of work benefits only	oowbben
- in work benefits only	inwbben
- both oow and in work benefits	bothbben
Proportion of time working 16+ hrs per week in 2 years pre – ONE:	
- **no time**	**pr160**
- up to 33% time	pr16133
- 34%-66% time	pr163466
- 67% to 99% time	pr166799
- all of time	pr16100
- No information	pr16dk
Proportion of time working 1-15 hrs per week in 2 years pre – ONE:	
- **no time**	**pr150**
- up to half time	pr15150
- over half time	pr1550p
Ever worked before*	evwkber
Any time in last 2 years spent*:	
- unemployed	anyunemr
- temporary sick/disabled**	anyillr
- long-term sick/disabled**	anysickr
- in training	anytrair
- in education	anyeducr
- in other activity	anyothr
Net pay per week in pre-ONE job:	
- **<£110 pw**	**npu110**
- £110-£149 pw	np110149
- £150-184 pw	np150184
- £185-254 pw	np185254
- £255+ pw	np255p
- no job or no information	npdk

Continued

Table C.1 Continued

Variable	Abbreviation
Social class in last job before entry date:	
- **professional or intermediate**	**profint**
- skilled non-manual worker	skillnm
- skilled manual worker	skillman
- partly skilled manual	partskil
- unskilled manual	unskill
- no job or Armed Forces	nojarmed
Care responsibilities	
- **no responsibility or no information**	**nocare**
- yes but doesn't affect work	carenaff
- yes and affects work	careaff
Receives regular income other than earnings/benefits:*	
- child support	chsupp
- other	othincm
- private pension	privpen
Number of workers in household excluding respondent:	
- **none**	**hhwker0**
- one	hhwker1
- two or more	hhwker2p
General health perceived:	
- **good**	**ghgood**
- fair	ghfair
- not good	ghnotg
Long-standing illness disability:	
- **does not have**	**lsino**
- yes but has no affect on ability to work	lsinoaff
- yes and affects ability to work	lsiaff
Mental disability*	mentdis
Possesses telephone*	phoner
Driving licence and vehicle access:	
- **has no licence**	**nolic**
- has licence but no vehicle access	licnoveh
- has both	licandv
Attitude towards work	
- **very negative**	**wavneglp**
- **fairly negative**	**wafneglp**
- middling	wamidlp
- fairly positive	wafposlp
- very positive	wavposlp

Continued

Table C.1 Continued

Variable	Abbreviation
TTWA characteristics	
The unemployment rate in 1999	uerate99
The change in the unemployment rate (comparing the rate in January to March 1999 with the rate in January to March 2000)	uechange
The total number of claimants of Incapacity Benefit, Disability Living Allowance, Severe Disablement Allowance, and Income Support claimed with a Disability Premium expressed as a proportion of the total workforce	disabpc
The change in the disability total as a percentage of the workforce, comparing February 2000 and May 2000	chansick
Lone parents claiming Income Support (without a Disability Premium) as a proportion of the total workforce	lonepc
The change in this proportion between February 2000 and May 2000	chanlp
24 benefit/model type areas	
- **benefit area 1**	**_Ibenarea_1**
- benefit areas 2-24	_ibenarea_
6 benefit/model type area	
- **Basic/ONE**	**basicone**
- Basic/Control	basiccon
- Call Centre/ONE	callone
- Call Centre/Control	callcon
- PVS/ONE	pvsone
- PVS/Control	pvscon

* These dummy variables are equal to 1 if true and 0 otherwise.

** Variable anysikil is used when we construct models predicting employment outcomes; variables anysickr and anyillr are used when we construct models predicting benefit outcomes.

Table C.2 Logit estimates for out-of-work status twelve months after their claim for benefit, JSA clients

	(1)	(2)	(3)	(4)	(5)	(6)
fem	-0.247	-0.233	-0.249	-0.234	-0.308	-0.280
	(1.95)	(1.82)	(1.97)*	(1.83)	(2.35)*	(2.12)*
age2024	-0.672	-0.654	-0.661	-0.655	-0.621	-0.618
	(3.55)**	(3.38)**	(3.47)**	(3.36)**	(3.11)**	(3.02)**
age2529	-0.411	-0.415	-0.399	-0.425	-0.378	-0.395
	(1.80)	(1.79)	(1.71)	(1.79)	(1.51)	(1.53)
age3034	-0.304	-0.259	-0.294	-0.280	-0.151	-0.161
	(1.28)	(1.08)	(1.20)	(1.12)	(0.58)	(0.60)
age3539	-0.222	-0.184	-0.218	-0.206	-0.119	-0.118
	(0.91)	(0.74)	(0.86)	(0.80)	(0.44)	(0.42)
age4044	-0.614	-0.611	-0.604	-0.622	-0.644	-0.671
	(2.36)*	(2.28)*	(2.26)*	(2.26)*	(2.27)*	(2.30)*
age4549	-0.256	-0.230	-0.242	-0.244	-0.280	-0.301
	(0.94)	(0.82)	(0.87)	(0.85)	(0.94)	(0.98)
age5054	-0.317	-0.267	-0.303	-0.278	-0.352	-0.352
	(1.17)	(0.96)	(1.09)	(0.98)	(1.16)	(1.13)
age5560	0.119	0.184	0.129	0.166	0.042	0.025
	(0.42)	(0.62)	(0.44)	(0.55)	(0.13)	(0.08)
white	-0.613	-0.550	-0.619	-0.548	-0.622	-0.563
	(3.07)**	(2.55)*	(3.12)**	(2.54)*	(2.98)**	(2.50)*
degree	-0.960	-1.002	-0.968	-0.981	-0.845	-0.857
	(4.79)**	(4.83)**	(4.64)**	(4.58)**	(3.77)**	(3.76)**

Continued

Table C.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
abovea	-0.368	-0.381	-0.364	-0.363	-0.282	-0.289
	(2.02)*	(2.06)*	(1.98)*	(1.93)	(1.46)	(1.48)
alev	-0.521	-0.502	-0.513	-0.480	-0.493	-0.476
	(2.97)**	(2.78)**	(2.91)**	(2.64)**	(2.61)**	(2.44)*
gcseac	-0.377	-0.364	-0.368	-0.346	-0.263	-0.254
	(2.46)*	(2.33)*	(2.40)*	(2.20)*	(1.62)	(1.53)
gcsede	-0.326	-0.301	-0.330	-0.301	-0.331	-0.280
	(1.69)	(1.57)	(1.71)	(1.57)	(1.67)	(1.41)
foreign	-0.317	-0.262	-0.318	-0.262	-0.347	-0.298
	(1.33)	(1.09)	(1.34)	(1.09)	(1.34)	(1.15)
num	0.236	0.253	0.244	0.258	0.124	0.128
	(1.16)	(1.23)	(1.20)	(1.26)	(0.56)	(0.58)
litr	0.187	0.196	0.187	0.198	0.222	0.232
	(1.01)	(1.03)	(1.01)	(1.04)	(1.14)	(1.17)
rentla	0.544	0.535	0.554	0.545	0.349	0.331
	(3.13)**	(3.05)**	(3.17)**	(3.10)**	(1.85)	(1.75)
rentha	-0.070	0.005	-0.067	0.007	-0.122	-0.144
	(0.29)	(0.02)	(0.28)	(0.03)	(0.49)	(0.57)
rentpriv	0.184	0.293	0.184	0.296	0.117	0.165
	(0.90)	(1.43)	(0.90)	(1.43)	(0.53)	(0.75)
tenoth	0.013	0.060	0.013	0.063	0.219	0.224
	(0.07)	(0.31)	(0.07)	(0.33)	(1.05)	(1.06)
tenin	0.648	0.907	0.674	0.926	0.772	0.944
	(1.11)	(1.54)	(1.14)	(1.55)	(1.45)	(1.73)
yng34	-0.772	-0.788	-0.770	-0.791	-0.751	-0.762
	(1.89)	(1.99)*	(1.88)	(1.98)*	(1.82)	(1.90)
yng510	-0.292	-0.355	-0.282	-0.343	-0.156	-0.220
	(1.00)	(1.21)	(0.97)	(1.17)	(0.51)	(0.72)
yng1118	-0.552	-0.537	-0.545	-0.528	-0.308	-0.319
	(1.75)	(1.69)	(1.73)	(1.66)	(0.93)	(0.95)
yngnokid	-0.338	-0.377	-0.343	-0.381	-0.258	-0.302
	(1.41)	(1.57)	(1.43)	(1.58)	(1.01)	(1.18)
oowbben	0.450	0.430	0.438	0.407	0.405	0.382
	(3.24)**	(3.03)**	(3.03)**	(2.77)**	(2.75)**	(2.56)*
inwbben	-0.172	-0.238	-0.171	-0.234	-0.276	-0.348
	(0.66)	(0.90)	(0.65)	(0.88)	(0.97)	(1.19)
bothbben	-0.198	-0.149	-0.214	-0.172	-0.283	-0.254
	(0.73)	(0.54)	(0.77)	(0.61)	(0.99)	(0.88)
pr16133	-0.281	-0.330	-0.294	-0.342	-0.205	-0.233
	(1.33)	(1.54)	(1.39)	(1.59)	(0.89)	(1.01)
pr163466	-0.365	-0.341	-0.367	-0.346	-0.124	-0.133
	(1.75)	(1.59)	(1.74)	(1.60)	(0.57)	(0.60)
pr166799	-0.738	-0.720	-0.727	-0.731	-0.420	-0.453
	(3.91)**	(3.72)**	(3.67)**	(3.61)**	(2.01)*	(2.15)*
pr16100	-0.759	-0.767	-0.666	-0.696	-0.382	-0.430
	(3.59)**	(3.60)**	(2.71)**	(2.81)**	(1.51)	(1.69)
pr16dk	-0.684	-0.654	-0.586	-0.576	-0.339	-0.366
	(3.32)**	(3.12)**	(2.40)*	(2.33)*	(1.35)	(1.44)
pr15150	-0.467	-0.435	-0.453	-0.432	-0.588	-0.604
	(1.45)	(1.30)	(1.39)	(1.27)	(1.56)	(1.51)
pr1550p	-0.904	-0.873	-0.843	-0.836	-0.776	-0.776
	(2.06)*	(1.99)*	(1.87)	(1.86)	(1.57)	(1.64)

Continued

Table C.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
evwkber	0.025	0.026	0.028	0.017	-0.037	-0.024
	(0.06)	(0.06)	(0.07)	(0.04)	(0.09)	(0.06)
anyunemr	0.294	0.282	0.369	0.360	0.343	0.333
	(1.92)	(1.84)	(2.18)*	(2.12)*	(1.98)*	(1.91)
np110149	-0.065	-0.011	-0.064	-0.017	-0.015	0.011
	(0.36)	(0.06)	(0.35)	(0.09)	(0.08)	(0.05)
np150184	-0.520	-0.429	-0.522	-0.436	-0.426	-0.375
	(2.79)**	(2.27)*	(2.78)**	(2.29)*	(2.18)*	(1.89)
np185254	-0.422	-0.341	-0.425	-0.349	-0.287	-0.233
	(2.18)*	(1.75)	(2.19)*	(1.79)	(1.41)	(1.13)
np255p	-0.382	-0.244	-0.383	-0.254	-0.202	-0.100
	(1.83)	(1.15)	(1.83)	(1.19)	(0.92)	(0.45)
npdk	0.205	0.281	0.213	0.279	0.268	0.306
	(0.64)	(0.89)	(0.67)	(0.88)	(0.80)	(0.91)
married	-0.588	-0.591	-0.587	-0.587	-0.372	-0.372
	(3.14)**	(3.14)**	(3.13)**	(3.12)**	(1.77)	(1.79)
cohab	-0.076	-0.054	-0.074	-0.055	0.074	0.081
	(0.38)	(0.27)	(0.37)	(0.28)	(0.35)	(0.38)
widowed	-0.521	-0.569	-0.522	-0.571	-0.270	-0.367
	(0.87)	(1.02)	(0.87)	(1.02)	(0.42)	(0.63)
divorced	0.010	0.029	0.011	0.027	0.046	0.021
	(0.04)	(0.13)	(0.05)	(0.12)	(0.20)	(0.09)
separ	0.084	0.010	0.084	0.002	0.067	0.009
	(0.32)	(0.04)	(0.31)	(0.01)	(0.25)	(0.03)
skillnm	-0.243	-0.280	-0.248	-0.285	-0.296	-0.334
	(1.25)	(1.44)	(1.28)	(1.46)	(1.47)	(1.65)
skillman	-0.099	-0.166	-0.108	-0.172	-0.255	-0.283
	(0.52)	(0.86)	(0.57)	(0.89)	(1.26)	(1.40)
partskil	0.067	0.035	0.063	0.032	-0.050	-0.072
	(0.35)	(0.19)	(0.33)	(0.17)	(0.26)	(0.36)
unskill	0.137	0.140	0.135	0.138	-0.081	-0.066
	(0.56)	(0.56)	(0.55)	(0.55)	(0.31)	(0.25)
nojarmed	-0.571	-0.659	-0.584	-0.676	-0.726	-0.779
	(1.99)*	(2.24)*	(2.04)*	(2.29)*	(2.45)*	(2.56)*
anyillr			0.171	0.161	-0.014	-0.044
			(0.72)	(0.67)	(0.06)	(0.18)
anysickr			0.312	0.356	-0.403	-0.354
			(0.66)	(0.76)	(0.73)	(0.66)
anytrair			-0.103	-0.151	-0.169	-0.194
			(0.47)	(0.69)	(0.70)	(0.80)
anyeducr			0.105	0.036	0.216	0.167
			(0.54)	(0.18)	(1.07)	(0.82)
anyothr			0.091	0.153	0.061	0.105
			(0.47)	(0.79)	(0.31)	(0.54)
disabpc					-0.010	-0.047
					(0.48)	(1.06)
chansick					-0.258	-0.077
					(0.82)	(0.21)
lonepc					0.020	0.123
					(0.16)	(0.75)
chanlp					0.584	0.699
					(1.16)	(1.22)

Continued

Table C.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
uerate99					0.073	0.009
					(1.46)	(0.11)
uechange					-0.250	-0.376
					(1.03)	(1.18)
carenaff					-0.026	-0.006
					(0.20)	(0.04)
careaff					0.800	0.855
					(2.59)**	(2.75)**
chsupp					-0.074	-0.135
					(0.14)	(0.25)
privpen					0.229	0.217
					(0.81)	(0.76)
othincm					0.563	0.558
					(2.72)**	(2.59)**
hhwker1					-0.049	-0.059
					(0.34)	(0.41)
hhwker2p					-0.566	-0.587
					(3.27)**	(3.31)**
ghfair					0.016	0.039
					(0.12)	(0.30)
ghnotg					0.711	0.709
					(3.69)**	(3.68)**
lsinoaff					-0.512	-0.491
					(2.46)*	(2.34)*
lsiaff					0.337	0.325
					(1.95)	(1.88)
mentdis					-0.187	-0.183
					(0.74)	(0.72)
phoner					-1.060	-1.081
					(4.16)**	(4.24)**
licnoveh					-0.213	-0.200
					(1.18)	(1.09)
licandv					-0.689	-0.681
					(5.03)**	(4.88)**
wafneg					-0.113	-0.090
					(0.74)	(0.58)
wamid					-0.443	-0.470
					(2.70)**	(2.85)**
wafpos					-0.416	-0.427
					(2.40)*	(2.45)*
wavpos					-0.646	-0.654
					(3.93)**	(3.87)**
basiccon	-0.120		-0.122		-0.039	
	(0.67)		(0.68)		(0.20)	
callone	0.062		0.069		0.186	
	(0.34)		(0.38)		(0.94)	
callcon	0.037		0.049		0.081	
	(0.21)		(0.27)		(0.40)	
pvsone	-0.054		-0.048		0.077	
	(0.31)		(0.28)		(0.40)	
pvscon	-0.025		-0.019		-0.037	
	(0.15)		(0.11)		(0.19)	

Continued

Table C.2 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
_Ibenarea_2		-0.153		-0.147		0.126
		(0.36)		(0.34)		(0.24)
_Ibenarea_3		0.388		0.387		0.922
		(0.98)		(0.97)		(1.46)
_Ibenarea_4		0.649		0.643		0.552
		(1.42)		(1.40)		(1.09)
_Ibenarea_5		0.411		0.422		0.763
		(0.95)		(0.97)		(1.50)
_Ibenarea_6		-0.086		-0.081		0.127
		(0.20)		(0.18)		(0.25)
_Ibenarea_7		0.603		0.609		0.985
		(1.40)		(1.41)		(1.69)
_Ibenarea_8		0.286		0.295		0.466
		(0.72)		(0.73)		(0.96)
_Ibenarea_9		-0.158		-0.155		0.166
		(0.40)		(0.39)		(0.34)
_Ibenarea_10		0.096		0.104		0.682
		(0.23)		(0.25)		(1.13)
_Ibenarea_11		0.397		0.397		0.589
		(1.01)		(1.00)		(1.25)
_Ibenarea_12		0.360		0.366		0.811
		(0.89)		(0.90)		(1.50)
_Ibenarea_13		-0.177		-0.187		-0.088
		(0.42)		(0.44)		(0.19)
_Ibenarea_14		-0.367		-0.385		-0.219
		(0.78)		(0.81)		(0.39)
_Ibenarea_15		0.731		0.740		1.155
		(1.77)		(1.78)		(2.15)*
_Ibenarea_16		0.068		0.071		0.358
		(0.17)		(0.17)		(0.73)
_Ibenarea_17		0.329		0.336		0.611
		(0.71)		(0.72)		(1.11)
_Ibenarea_18		0.119		0.141		0.457
		(0.26)		(0.31)		(0.85)
_Ibenarea_19		0.079		0.088		0.344
		(0.19)		(0.22)		(0.68)
_Ibenarea_20		0.456		0.463		0.461
		(1.19)		(1.19)		(0.92)
_Ibenarea_21		-0.126		-0.146		0.080
		(0.31)		(0.36)		(0.16)
_Ibenarea_22		0.007		0.002		0.409
		(0.02)		(0.00)		(0.71)
_Ibenarea_23		0.301		0.320		0.549
		(0.75)		(0.80)		(0.99)
_Ibenarea_24		0.638		0.668		0.814
		(1.53)		(1.60)		(1.64)
Constant	1.927	1.584	1.827	1.525	2.611	2.525
	(3.19)**	(2.34)*	(2.91)**	(2.17)*	(3.60)**	(2.97)**
Observations	2232	2232	2232	2232	2232	2232

Table C.3 Logit estimates for out-of-work benefit receipt twelve months after their claim for benefit, JSA clients

	(1)	(2)	(3)	(4)	(5)	(6)
fem	-0.222	-0.209	-0.200	-0.184	-0.220	-0.202
	(1.62)	(1.51)	(1.45)	(1.33)	(1.52)	(1.40)
age2024	-0.417	-0.397	-0.457	-0.446	-0.382	-0.389
	(2.10)*	(1.98)*	(2.27)*	(2.19)*	(1.77)	(1.79)
age2529	-0.072	-0.049	-0.144	-0.138	-0.077	-0.083
	(0.30)	(0.20)	(0.58)	(0.55)	(0.29)	(0.31)
age3034	0.292	0.340	0.210	0.241	0.403	0.395
	(1.16)	(1.34)	(0.81)	(0.92)	(1.47)	(1.43)
age3539	0.257	0.277	0.188	0.189	0.445	0.410
	(0.95)	(1.02)	(0.68)	(0.68)	(1.51)	(1.38)
age4044	-0.188	-0.171	-0.266	-0.271	-0.182	-0.234
	(0.65)	(0.58)	(0.90)	(0.90)	(0.58)	(0.73)
age4549	0.413	0.436	0.332	0.334	0.423	0.394
	(1.37)	(1.42)	(1.09)	(1.07)	(1.27)	(1.16)
age5054	0.374	0.435	0.274	0.322	0.356	0.374
	(1.24)	(1.43)	(0.89)	(1.03)	(1.05)	(1.09)
age5560	0.397	0.437	0.326	0.349	0.339	0.311
	(1.22)	(1.31)	(0.99)	(1.04)	(0.95)	(0.86)
white	-0.136	0.002	-0.113	0.020	-0.059	0.073
	(0.66)	(0.01)	(0.54)	(0.09)	(0.27)	(0.32)
degree	-1.566	-1.590	-1.456	-1.462	-1.258	-1.253
	(6.22)**	(6.18)**	(5.62)**	(5.53)**	(4.53)**	(4.43)**
abovea	-0.702	-0.701	-0.665	-0.656	-0.576	-0.560
	(3.42)**	(3.38)**	(3.17)**	(3.10)**	(2.63)**	(2.54)*
alev	-0.518	-0.491	-0.486	-0.448	-0.378	-0.332
	(2.72)**	(2.53)*	(2.53)*	(2.29)*	(1.87)	(1.61)
gcseac	-0.264	-0.271	-0.242	-0.244	-0.103	-0.118
	(1.61)	(1.63)	(1.46)	(1.45)	(0.59)	(0.67)
gcsede	-0.187	-0.148	-0.149	-0.104	-0.080	-0.027
	(0.91)	(0.72)	(0.72)	(0.50)	(0.36)	(0.12)
foreign	-0.201	-0.207	-0.181	-0.182	-0.103	-0.106
	(0.85)	(0.86)	(0.75)	(0.74)	(0.40)	(0.41)
num	0.436	0.452	0.424	0.446	0.279	0.288
	(2.00)*	(2.05)*	(1.93)	(2.01)*	(1.16)	(1.21)
litr	0.031	0.053	0.042	0.066	0.106	0.106
	(0.15)	(0.25)	(0.20)	(0.32)	(0.49)	(0.49)
rentla	1.105	1.120	1.099	1.113	0.792	0.800
	(5.75)**	(5.79)**	(5.71)**	(5.74)**	(3.94)**	(3.96)**
rentha	0.418	0.521	0.402	0.505	0.242	0.270
	(1.60)	(1.95)	(1.54)	(1.88)	(0.88)	(0.97)
rentpriv	0.673	0.784	0.679	0.796	0.537	0.584
	(3.04)**	(3.44)**	(3.06)**	(3.50)**	(2.29)*	(2.43)*
tenoth	0.330	0.375	0.323	0.370	0.479	0.498
	(1.53)	(1.70)	(1.50)	(1.68)	(2.08)*	(2.12)*
tenin	1.706	1.851	1.632	1.777	1.521	1.588
	(2.59)**	(2.77)**	(2.50)*	(2.69)**	(2.63)**	(2.65)**
yng34	-0.435	-0.452	-0.455	-0.472	-0.296	-0.323
	(1.02)	(1.07)	(1.06)	(1.11)	(0.71)	(0.79)
yng510	-0.366	-0.369	-0.385	-0.381	-0.192	-0.188
	(1.16)	(1.14)	(1.21)	(1.17)	(0.57)	(0.55)

Continued

Table C.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
yng1118	-0.436	-0.409	-0.473	-0.439	-0.184	-0.182
	(1.30)	(1.20)	(1.40)	(1.28)	(0.52)	(0.51)
yngnokid	-0.383	-0.399	-0.378	-0.396	-0.197	-0.223
	(1.43)	(1.48)	(1.42)	(1.48)	(0.71)	(0.80)
oowbben	0.733	0.707	0.716	0.678	0.629	0.590
	(4.87)**	(4.64)**	(4.57)**	(4.29)**	(3.84)**	(3.58)**
inwbben	-0.316	-0.297	-0.312	-0.297	-0.408	-0.440
	(1.06)	(1.00)	(1.04)	(1.00)	(1.24)	(1.35)
bothbben	0.492	0.508	0.485	0.494	0.380	0.397
	(1.73)	(1.76)	(1.69)	(1.70)	(1.29)	(1.34)
pr16133	-0.392	-0.408	-0.357	-0.373	-0.312	-0.336
	(1.72)	(1.76)	(1.56)	(1.60)	(1.29)	(1.36)
pr163466	-0.294	-0.266	-0.291	-0.265	-0.039	-0.046
	(1.31)	(1.16)	(1.28)	(1.14)	(0.17)	(0.19)
pr166799	-0.694	-0.683	-0.745	-0.749	-0.420	-0.462
	(3.28)**	(3.14)**	(3.33)**	(3.26)**	(1.78)	(1.93)
pr16100	-0.568	-0.593	-0.775	-0.819	-0.437	-0.506
	(2.37)*	(2.45)*	(2.81)**	(2.94)**	(1.53)	(1.76)
pr16dk	-0.793	-0.784	-0.996	-1.002	-0.748	-0.782
	(3.40)**	(3.28)**	(3.67)**	(3.60)**	(2.64)**	(2.72)**
pr15150	-0.240	-0.261	-0.290	-0.312	-0.358	-0.428
	(0.75)	(0.80)	(0.92)	(0.96)	(1.00)	(1.15)
pr1550p	-0.083	-0.095	-0.257	-0.285	-0.229	-0.310
	(0.16)	(0.18)	(0.49)	(0.53)	(0.40)	(0.54)
evwkber	-0.125	-0.146	-0.137	-0.147	-0.206	-0.217
	(0.27)	(0.31)	(0.29)	(0.31)	(0.40)	(0.43)
anyunemr	-0.076	-0.076	-0.192	-0.194	-0.180	-0.177
	(0.46)	(0.45)	(1.07)	(1.07)	(0.97)	(0.96)
np110149	-0.221	-0.207	-0.244	-0.234	-0.248	-0.251
	(1.18)	(1.09)	(1.30)	(1.22)	(1.27)	(1.26)
np150184	-0.275	-0.240	-0.288	-0.253	-0.221	-0.224
	(1.41)	(1.20)	(1.46)	(1.26)	(1.09)	(1.09)
np185254	-0.467	-0.432	-0.469	-0.435	-0.353	-0.353
	(2.32)*	(2.14)*	(2.33)*	(2.16)*	(1.65)	(1.64)
np255p	-0.416	-0.362	-0.421	-0.365	-0.286	-0.258
	(1.83)	(1.56)	(1.85)	(1.57)	(1.15)	(1.03)
npdk	0.320	0.365	0.297	0.343	0.229	0.247
	(0.89)	(1.01)	(0.82)	(0.94)	(0.60)	(0.65)
married	-0.902	-0.911	-0.906	-0.918	-0.592	-0.565
	(4.27)**	(4.23)**	(4.32)**	(4.29)**	(2.50)*	(2.36)*
cohab	-0.528	-0.541	-0.547	-0.562	-0.314	-0.329
	(2.40)*	(2.45)*	(2.48)*	(2.53)*	(1.32)	(1.38)
widowed	0.480	0.660	0.479	0.656	0.829	0.961
	(0.67)	(0.94)	(0.67)	(0.94)	(1.10)	(1.32)
divorced	0.155	0.196	0.136	0.173	0.159	0.175
	(0.65)	(0.81)	(0.57)	(0.71)	(0.63)	(0.68)
separ	0.007	-0.046	-0.008	-0.068	0.029	-0.032
	(0.02)	(0.15)	(0.03)	(0.22)	(0.10)	(0.11)
skillnm	-0.142	-0.147	-0.127	-0.126	-0.195	-0.176
	(0.62)	(0.63)	(0.56)	(0.54)	(0.82)	(0.73)
skillman	0.050	0.020	0.076	0.047	-0.053	-0.028
	(0.23)	(0.09)	(0.34)	(0.21)	(0.23)	(0.12)

Continued

Table C.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
partskil	0.180	0.174	0.203	0.198	0.099	0.133
	(0.82)	(0.78)	(0.92)	(0.89)	(0.43)	(0.57)
unskill	0.212	0.183	0.240	0.212	0.035	0.064
	(0.80)	(0.67)	(0.90)	(0.78)	(0.12)	(0.23)
nojarmed	-0.633	-0.695	-0.592	-0.652	-0.699	-0.729
	(1.96)*	(2.13)*	(1.82)	(1.99)*	(2.01)*	(2.06)*
anyillr			-0.408	-0.397	-0.642	-0.625
			(1.65)	(1.61)	(2.56)*	(2.50)*
anysickr			0.209	0.175	-0.373	-0.390
			(0.39)	(0.30)	(0.56)	(0.57)
anytrair			0.135	0.105	0.055	0.025
			(0.63)	(0.48)	(0.24)	(0.10)
anyeducr			-0.388	-0.445	-0.244	-0.289
			(1.94)	(2.20)*	(1.14)	(1.33)
anyothr			-0.083	-0.050	-0.091	-0.060
			(0.39)	(0.23)	(0.42)	(0.28)
disabpc					0.004	0.030
					(0.17)	(0.64)
chansick					0.444	0.568
					(1.29)	(1.48)
lonepc					0.138	0.121
					(1.01)	(0.67)
chanlp					0.950	0.731
					(1.81)	(1.20)
uerate99					0.013	-0.011
					(0.24)	(0.13)
uechange					-0.396	-0.711
					(1.46)	(1.98)*
carenaff					0.279	0.273
					(1.96)	(1.89)
careaff					0.886	0.854
					(2.94)**	(2.81)**
chsupp					-0.757	-0.829
					(1.21)	(1.28)
privpen					0.084	0.073
					(0.24)	(0.21)
othincm					-0.109	-0.164
					(0.41)	(0.62)
hhwker1					-0.397	-0.413
					(2.51)*	(2.57)*
hhwker2p					-0.692	-0.693
					(3.74)**	(3.71)**
ghfair					0.213	0.209
					(1.55)	(1.50)
ghnotg					0.843	0.829
					(4.19)**	(4.08)**
lsinoaff					-0.513	-0.490
					(2.26)*	(2.12)*
lsiaff					0.167	0.174
					(0.92)	(0.94)
mentdis					0.000	-0.005
					(0.00)	(0.02)

Continued

Table C.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
phoner					-0.801	-0.853
					(3.48)**	(3.72)**
licnoveh					-0.316	-0.317
					(1.64)	(1.62)
licandv					-0.672	-0.672
					(4.53)**	(4.46)**
wafneg					-0.089	-0.095
					(0.54)	(0.58)
wamid					-0.230	-0.237
					(1.30)	(1.33)
wafpos					-0.430	-0.457
					(2.30)*	(2.43)*
wavpos					-0.638	-0.642
					(3.49)**	(3.44)**
basiccon	0.011		0.007		0.124	
	(0.05)		(0.04)		(0.58)	
callone	0.234		0.221		0.355	
	(1.17)		(1.10)		(1.63)	
callcon	0.329		0.300		0.377	
	(1.67)		(1.51)		(1.73)	
pvsone	-0.111		-0.122		0.049	
	(0.57)		(0.63)		(0.23)	
pvscon	-0.020		-0.040		-0.093	
	(0.10)		(0.21)		(0.43)	
_Ibenarea_2		-0.351		-0.339		0.108
		(0.79)		(0.76)		(0.20)
_Ibenarea_3		-0.326		-0.279		-0.482
		(0.78)		(0.68)		(0.74)
_Ibenarea_4		0.408		0.417		0.482
		(0.83)		(0.84)		(0.94)
_Ibenarea_5		0.135		0.142		0.491
		(0.30)		(0.32)		(0.96)
_Ibenarea_6		-0.287		-0.273		0.277
		(0.61)		(0.58)		(0.52)
_Ibenarea_7		0.284		0.298		0.312
		(0.65)		(0.68)		(0.53)
_Ibenarea_8		0.249		0.249		0.405
		(0.62)		(0.62)		(0.85)
_Ibenarea_9		-0.796		-0.800		-0.375
		(1.92)		(1.96)		(0.77)
_Ibenarea_10		0.016		0.048		0.239
		(0.04)		(0.11)		(0.39)
_Ibenarea_11		-0.253		-0.254		0.059
		(0.62)		(0.63)		(0.12)
_Ibenarea_12		0.194		0.219		0.348
		(0.45)		(0.51)		(0.60)
_Ibenarea_13		-0.053		-0.058		0.345
		(0.12)		(0.13)		(0.74)
_Ibenarea_14		-0.350		-0.362		-0.031
		(0.70)		(0.73)		(0.05)
_Ibenarea_15		-0.051		0.029		0.465
		(0.12)		(0.07)		(0.86)

Continued

Table C.3 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
_Ibenarea_16		-0.075		-0.069		-0.099
		(0.19)		(0.17)		(0.20)
_Ibenarea_17		0.114		0.089		0.732
		(0.22)		(0.17)		(1.29)
_Ibenarea_18		0.036		-0.010		0.490
		(0.08)		(0.02)		(0.95)
_Ibenarea_19		0.148		0.175		0.504
		(0.35)		(0.42)		(1.00)
_Ibenarea_20		0.374		0.367		0.129
		(0.95)		(0.94)		(0.26)
_Ibenarea_21		-0.739		-0.741		-0.454
		(1.68)		(1.69)		(0.89)
_Ibenarea_22		-0.046		-0.040		-0.064
		(0.11)		(0.10)		(0.11)
_Ibenarea_23		-0.035		-0.043		-0.345
		(0.08)		(0.10)		(0.61)
_Ibenarea_24		0.215		0.225		0.205
		(0.52)		(0.54)		(0.42)
Constant	0.381	0.328	0.626	0.576	0.661	0.394
	(0.56)	(0.44)	(0.89)	(0.75)	(0.82)	(0.43)
Observations	2232	2232	2232	2232	2232	2232

Table C.4 OLS estimates of percentage of time JSA clients spend on out-of-work benefits, DSSDTE-31/12/02

	(1)	(2)	(3)	(4)	(5)	(6)
fem	-2.654	-2.486	-2.666	-2.497	-2.845	-2.837
	(2.22)*	(2.07)*	(2.22)*	(2.08)*	(2.34)*	(2.32)*
age2024	-2.115	-1.896	-2.703	-2.611	-2.096	-2.212
	(1.13)	(1.01)	(1.43)	(1.38)	(1.10)	(1.16)
age2529	0.240	0.597	-0.960	-0.789	-0.176	-0.078
	(0.10)	(0.26)	(0.41)	(0.34)	(0.07)	(0.03)
age3034	1.085	1.364	-0.230	-0.179	0.575	0.508
	(0.44)	(0.56)	(0.09)	(0.07)	(0.23)	(0.20)
age3539	-0.882	-0.671	-2.495	-2.482	-1.773	-1.920
	(0.33)	(0.25)	(0.92)	(0.92)	(0.65)	(0.70)
age4044	-0.774	-0.522	-2.205	-2.156	-1.431	-1.668
	(0.30)	(0.20)	(0.84)	(0.82)	(0.54)	(0.62)
age4549	3.936	4.013	2.653	2.517	3.477	3.096
	(1.34)	(1.36)	(0.89)	(0.84)	(1.15)	(1.02)
age5054	-0.319	0.106	-1.557	-1.312	-0.786	-1.102
	(0.11)	(0.04)	(0.52)	(0.43)	(0.25)	(0.35)
age5560	2.272	2.811	0.710	1.072	1.646	1.458
	(0.73)	(0.90)	(0.23)	(0.34)	(0.50)	(0.44)
white	-0.163	-1.454	-0.108	-1.394	-0.384	-0.852
	(0.09)	(0.77)	(0.06)	(0.74)	(0.21)	(0.45)
degree	-3.669	-3.904	-2.257	-2.284	-0.060	-0.192
	(1.96)*	(2.10)*	(1.14)	(1.17)	(0.03)	(0.10)
abovea	-0.475	-1.068	0.278	-0.238	1.176	0.817
	(0.24)	(0.54)	(0.14)	(0.12)	(0.59)	(0.41)

Continued

Table C.4 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
alev	0.282	-0.078	1.142	0.877	2.154	1.933
	(0.16)	(0.04)	(0.63)	(0.48)	(1.17)	(1.05)
gcseac	-1.695	-1.435	-1.185	-0.848	-0.509	-0.363
	(1.04)	(0.88)	(0.72)	(0.52)	(0.31)	(0.22)
gcsede	2.816	2.545	3.085	2.880	3.279	2.980
	(1.34)	(1.22)	(1.47)	(1.38)	(1.59)	(1.45)
foreign	-0.295	-0.073	-0.020	0.259	0.808	0.893
	(0.13)	(0.03)	(0.01)	(0.12)	(0.37)	(0.41)
num	2.959	3.365	3.113	3.547	2.626	2.800
	(1.30)	(1.50)	(1.38)	(1.60)	(1.17)	(1.25)
litr	1.994	2.122	2.203	2.365	1.897	1.911
	(1.06)	(1.13)	(1.17)	(1.26)	(1.01)	(1.02)
rentla	8.842	8.641	8.917	8.696	8.088	7.750
	(4.90)**	(4.76)**	(4.98)**	(4.84)**	(4.47)**	(4.25)**
rentha	5.527	5.930	5.635	6.079	5.965	5.532
	(2.08)*	(2.23)*	(2.12)*	(2.29)*	(2.26)*	(2.10)*
rentpriv	3.160	3.719	3.266	3.857	3.393	3.254
	(1.67)	(1.94)	(1.73)	(2.02)*	(1.77)	(1.69)
tenoth	3.606	3.668	3.765	3.843	4.435	3.910
	(1.93)	(1.95)	(2.02)*	(2.05)*	(2.29)*	(2.02)*
tenin	7.807	8.498	7.705	8.310	8.144	7.639
	(1.65)	(1.79)	(1.61)	(1.74)	(1.72)	(1.61)
yng34	-2.092	-2.960	-2.041	-2.952	-3.158	-3.568
	(0.62)	(0.88)	(0.61)	(0.88)	(0.96)	(1.08)
yng510	0.699	0.480	0.887	0.636	0.988	0.655
	(0.24)	(0.16)	(0.30)	(0.22)	(0.34)	(0.23)
yng1118	1.514	1.610	2.016	2.156	2.818	3.011
	(0.48)	(0.51)	(0.65)	(0.69)	(0.90)	(0.96)
yngnokid	4.357	3.789	4.776	4.205	4.516	4.254
	(1.82)	(1.58)	(1.99)*	(1.75)	(1.87)	(1.77)
oowbben	10.542	10.218	9.670	9.262	8.932	8.835
	(7.80)**	(7.55)**	(6.90)**	(6.59)**	(6.33)**	(6.23)**
inwbben	-1.392	-1.435	-1.140	-1.230	-1.318	-1.386
	(0.62)	(0.63)	(0.51)	(0.54)	(0.57)	(0.60)
bothbben	7.805	7.523	7.083	6.760	7.136	6.847
	(3.00)**	(2.88)**	(2.67)**	(2.54)*	(2.70)**	(2.58)**
pr16133	1.460	1.408	0.957	0.890	1.042	1.001
	(0.66)	(0.64)	(0.44)	(0.40)	(0.48)	(0.46)
pr163466	1.540	1.600	0.753	0.744	1.354	1.172
	(0.73)	(0.76)	(0.36)	(0.35)	(0.64)	(0.56)
pr166799	-1.711	-1.612	-3.159	-3.204	-2.184	-2.372
	(0.85)	(0.80)	(1.53)	(1.56)	(1.06)	(1.16)
pr16100	0.481	0.930	-0.559	-0.367	0.014	0.167
	(0.23)	(0.44)	(0.23)	(0.15)	(0.01)	(0.07)
pr16dk	-0.797	-0.412	-1.716	-1.581	-1.610	-1.582
	(0.37)	(0.19)	(0.69)	(0.64)	(0.65)	(0.64)
pr15150	-0.546	0.064	-0.812	-0.221	-1.406	-1.341
	(0.16)	(0.02)	(0.24)	(0.07)	(0.43)	(0.40)
pr1550p	8.530	8.794	7.472	7.462	8.348	8.417
	(1.60)	(1.65)	(1.39)	(1.39)	(1.57)	(1.58)
evwkber	0.482	0.750	-0.161	0.048	0.242	0.437
	(0.12)	(0.19)	(0.04)	(0.01)	(0.06)	(0.11)

Continued

Table C.4 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
anyunemr	1.773	2.021	2.414	2.586	2.196	2.319
	(1.14)	(1.29)	(1.40)	(1.49)	(1.29)	(1.34)
np110149	3.066	3.102	2.926	2.933	2.795	2.819
	(1.75)	(1.77)	(1.68)	(1.68)	(1.61)	(1.62)
np150184	3.678	4.096	3.336	3.743	3.630	3.706
	(2.02)*	(2.25)*	(1.85)	(2.08)*	(2.03)*	(2.06)*
np185254	0.695	1.129	0.546	0.966	1.169	1.237
	(0.37)	(0.60)	(0.29)	(0.52)	(0.62)	(0.66)
np255p	3.150	3.530	2.797	3.131	3.817	3.731
	(1.50)	(1.67)	(1.34)	(1.49)	(1.82)	(1.75)
npdk	0.097	0.412	-0.206	0.056	-0.112	-0.101
	(0.03)	(0.13)	(0.06)	(0.02)	(0.03)	(0.03)
married	-1.168	-1.715	-0.932	-1.491	-0.365	-0.970
	(0.60)	(0.88)	(0.48)	(0.76)	(0.17)	(0.46)
cohab	1.637	1.687	1.727	1.774	1.859	1.807
	(0.78)	(0.81)	(0.82)	(0.85)	(0.87)	(0.85)
widowed	1.799	0.916	1.931	0.998	2.026	1.357
	(0.34)	(0.17)	(0.36)	(0.19)	(0.38)	(0.25)
divorced	2.002	1.995	1.868	1.824	2.423	2.250
	(0.84)	(0.85)	(0.79)	(0.78)	(1.04)	(0.97)
separ	1.505	1.432	1.147	0.991	1.042	1.212
	(0.55)	(0.51)	(0.42)	(0.36)	(0.38)	(0.43)
skillnm	3.315	3.215	3.298	3.200	3.115	3.074
	(1.81)	(1.75)	(1.80)	(1.76)	(1.71)	(1.68)
skillman	3.798	3.204	3.804	3.217	2.945	2.941
	(2.11)*	(1.76)	(2.10)*	(1.76)	(1.62)	(1.61)
partskil	4.447	3.981	4.451	3.977	3.563	3.585
	(2.41)*	(2.16)*	(2.41)*	(2.16)*	(1.94)	(1.94)
unskill	6.686	6.359	6.555	6.214	5.275	5.352
	(2.81)**	(2.68)**	(2.77)**	(2.63)**	(2.22)*	(2.25)*
nojarmed	6.024	5.431	5.617	4.987	5.143	5.040
	(2.36)*	(2.13)*	(2.19)*	(1.94)	(1.98)*	(1.95)
anyillr			7.268	7.191	5.947	5.885
			(2.80)**	(2.79)**	(2.27)*	(2.25)*
anysickr			-7.224	-7.434	-8.181	-8.113
			(1.30)	(1.29)	(1.40)	(1.36)
anytrair			-4.433	-4.730	-4.909	-5.078
			(1.91)	(2.03)*	(2.12)*	(2.20)*
anyeducr			-3.090	-3.702	-3.029	-3.259
			(1.62)	(1.96)*	(1.60)	(1.72)
anyothr			0.825	1.053	0.880	0.830
			(0.42)	(0.53)	(0.45)	(0.42)
disabpc					0.445	0.027
					(2.17)*	(0.06)
chansick					-2.128	-3.632
					(0.68)	(1.01)
lonepc					-0.379	1.543
					(0.32)	(1.01)
chanlp					-3.760	-0.534
					(0.83)	(0.11)
uerate99					0.154	-0.657
					(0.33)	(0.88)

Continued

Table C.4 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
uechange					-2.591	-1.147
					(1.08)	(0.38)
carenaff					0.877	1.331
					(0.67)	(1.02)
careaff					4.098	4.399
					(1.31)	(1.41)
chsupp					-10.646	-10.743
					(3.31)**	(3.43)**
privpen					0.427	0.335
					(0.13)	(0.10)
othincm					-1.907	-1.614
					(0.98)	(0.83)
hhwker1					-0.225	-0.086
					(0.17)	(0.06)
hhwker2p					-1.784	-1.601
					(1.16)	(1.04)
ghfair					4.023	4.131
					(3.05)**	(3.13)**
ghnotg					5.077	5.205
					(2.59)**	(2.68)**
lsinoaff					0.980	0.717
					(0.51)	(0.37)
lsiaff					-0.940	-0.846
					(0.52)	(0.47)
mentdis					-2.552	-2.864
					(1.02)	(1.14)
phoner					-2.181	-2.259
					(1.20)	(1.24)
licnoveh					-2.404	-2.269
					(1.44)	(1.36)
licandv					-3.009	-2.895
					(2.34)*	(2.23)*
wafneg					-2.090	-1.955
					(1.45)	(1.37)
wamid					-1.679	-1.832
					(1.05)	(1.15)
wafpos					-1.721	-1.794
					(1.05)	(1.09)
wavpos					-1.761	-1.872
					(1.10)	(1.18)
basiccon	-3.476		-3.637		-2.059	
	(2.01)*		(2.10)*		(1.17)	
callone	-1.138		-1.285		0.106	
	(0.63)		(0.71)		(0.06)	
callcon	-2.289		-2.352		-0.760	
	(1.27)		(1.31)		(0.41)	
pvsone	-1.716		-1.770		-0.955	
	(0.98)		(1.01)		(0.54)	

Continued

Table C.4 Continued

	(1)	(2)	(3)	(4)	(5)	(6)
_Ibenarea_2		-5.191		-5.212		-3.344
		(1.45)		(1.47)		(0.83)
_Ibenarea_3		9.357		9.427		10.389
		(2.54)*		(2.58)**		(1.81)
_Ibenarea_4		-1.268		-1.063		-0.383
		(0.33)		(0.28)		(0.10)
_Ibenarea_5		0.278		0.116		2.884
		(0.07)		(0.03)		(0.68)
_Ibenarea_6		-2.083		-2.007		-0.318
		(0.57)		(0.55)		(0.08)
_Ibenarea_7		3.170		3.353		2.495
		(0.79)		(0.85)		(0.46)
_Ibenarea_8		0.415		0.069		1.138
		(0.12)		(0.02)		(0.30)
_Ibenarea_9		-0.683		-0.617		1.624
		(0.19)		(0.18)		(0.42)
_Ibenarea_10		-1.545		-1.390		0.028
		(0.42)		(0.38)		(0.01)
_Ibenarea_11		-0.592		-0.783		0.705
		(0.17)		(0.23)		(0.19)
_Ibenarea_12		2.854		2.941		4.187
		(0.73)		(0.76)		(0.87)
_Ibenarea_13		-4.594		-4.764		-3.002
		(1.36)		(1.42)		(0.88)
_Ibenarea_14		-3.115		-3.673		-2.067
		(0.80)		(0.96)		(0.50)
_Ibenarea_15		-0.219		0.224		2.990
		(0.06)		(0.06)		(0.68)
_Ibenarea_16		-0.759		-1.036		-0.665
		(0.22)		(0.30)		(0.16)
_Ibenarea_17		-2.025		-2.608		-1.221
		(0.49)		(0.64)		(0.27)
_Ibenarea_18		-3.539		-3.454		-1.915
		(0.93)		(0.92)		(0.47)
_Ibenarea_19		0.813		0.825		4.106
		(0.23)		(0.23)		(1.00)
_Ibenarea_20		0.145		0.357		2.033
		(0.04)		(0.11)		(0.51)
_Ibenarea_21		2.754		2.175		4.067
		(0.76)		(0.60)		(1.01)
_Ibenarea_22		1.428		1.054		2.191
		(0.39)		(0.29)		(0.43)
_Ibenarea_23		7.286		7.717		9.729
		(1.95)		(2.08)*		(1.95)
_Ibenarea_24		2.694		2.991		4.479
		(0.72)		(0.81)		(1.10)
Constant	12.975	12.683	15.095	15.210	11.176	13.297
	(2.12)*	(1.94)	(2.39)*	(2.28)*	(1.64)	(1.73)
Observations	3121	3121	3121	3121	3121	3121
R-squared	0.10	0.11	0.11	0.12	0.13	0.13

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