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**PROFILING THE
UNEMPLOYED:**

AN ANALYSIS OF THE
GALWAY AND
WATERFORD
LIVE-REGISTER SURVEYS

**RICHARD LAYTE
PHILIP O'CONNELL**

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EXECUTIVE SUMMARY

Introduction

In recent years economic development in Ireland has seen unemployment fall dramatically. Unemployment may no longer be the huge problem that it was to Irish society, but for each individual unemployed it can still present a personal crisis that can severely affect their living standards and future prospects. Because of this, governments have an obligation, both from a standpoint of expenditure efficiency and individual social welfare to help the unemployed get back into work.

Ireland has a very well developed system of ‘active labour market policies’ – training and subsidised employment for the unemployed that has helped many thousands of individuals back into work and for the last seven years has been operating the National Employment Action Plan (NEAP). The NEAP was first instituted on September 1st 1998 at which point all young people aged under 25 years who had reached six months on the Register were referred by the Department of Social and Family Affairs (DSFA) to FÁS for interview. Since then the process has been extended to broader groups of unemployed. From the evidence that is available (although NEAP has not yet been systematically evaluated) this process seems to have been very successful and suggests that a more proactive approach to the unemployed is beneficial. Yet, at the earliest, the NEAP only intervenes after a person has been on the Live Register for six months and there is the danger that their future prospects will already have been permanently scarred by the experience.

The Potential Benefits of Profiling

Most people who become unemployed find another job within a few months. However, a substantial minority, about 15 per cent at present, remain unemployed for a year or more and thus enter long-term unemployment. Many of those who become long-term unemployed suffer particular labour market disadvantages and would benefit from early assistance in retraining or job search. Profiling represents an attempt to overcome the dilemma between intervening early to assist those job seekers who will need assistance to find another job, but not wasting scarce public resources and jobseekers’ time by providing interventions to those who are likely to find a job on the basis of their own resources and efforts.

Profiling is a systematic approach to the early identification of individuals with high risk of becoming long-term unemployed which entails both (i) formal methods for identification of individuals at risk of becoming long-term unemployed; and (ii) their referral to

appropriate interventions. The basic idea involved in profiling is to develop a statistical model of the effects of a range of personal characteristics on the probability that any individual will become long-term unemployed. The results of these models can then be applied by officials of the public employment service to assess the probability of any individual unemployed client becoming long-term unemployed.

There are two main advantages to profiling. First, profiling allows for a more systematic and rigorous identification of those who have a high probability of suffering from employability difficulties, who may become long-term unemployed, and who might benefit from Active Labour Market Programme (ALMP) interventions. Second, profiling has the additional advantage of allowing for the ranking of individuals according to their estimated probability of becoming long-term unemployed. Given scarce resources and limited numbers of places on programmes, such a ranking can be used to determine eligibility for ALMP referral.

This report has two key aims. The first is to understand the processes that lead to exit from unemployment and in particular, exit from the Live Register. The second aim is to use this understanding of the processes leading to exit from the Register to develop a 'profile' of the unemployed that can be used by the DSFA to improve the service that they provide to customers and increase the efficiency and effectiveness of the welfare services and training provided by the public sector at large.

The Galway and Waterford Surveys of Unemployed

The study is based on data from several sources. Three surveys were conducted. Baseline surveys were conducted in 2000 of just over 1,400 customers on the Live Register in the Galway region, and just under 1,400 customers in the Waterford region. A follow-up survey was carried out in respect of the Galway sample in 2002. In addition to these survey data, administrative information from the Live Register was collected and combined with the survey data to allow comparison of outcomes between the surveys and the Live Register data. The baseline surveys collected information on a range of influential factors that are not routinely collected in the administration of the Live Register. The follow-up survey collected additional information on the Galway sample that was not available either from the baseline survey or the Live Register.

Our analysis of these data showed that there is a highly structured relationship between a relatively small number of personal characteristics and duration on the Live Register. Education plays a significant role: the lower the level of education of the respondent, the less likely it is that they will leave the Register to employment. For men, age is also important: men in older age groups find it more difficult to find employment and are far more likely to move from the Live Register on to a Community Employment Scheme or move into retirement. Having access to a form of transport also proved very important in helping men to leave the Register to employment, whereas having a larger number of children slowed down this

transition. Ill health and previous spells of unemployment or full-time caring also slow down exits from unemployment.

Having identified the influential factors in prolonged duration on the Live Register, we then incorporated such information into a predictive model that can be used to profile or identify those who are likely to become long-term unemployed. These profiling models were developed for the Galway region and proved extremely successful at predicting whether a person would become long-term unemployed although the models for men were more successful than those for women. The models for women were limited by the small number of cases that were available for analysis, but it also seems true that the factors behind female labour force participation are more complex than those for men since they tend to be influenced by domestic circumstances and the interaction of these with occupational career over the persons life to a far greater extent than is found for men. Among men the model correctly predicted around 75 per cent of all short-term stays on the Register and around 85 per cent of long-term stays with an overall prediction success rate of 84 per cent. Among women the full model correctly predicted around 64 per cent of short-term stays on the Register and 73 per cent of long-term stays leading to an overall prediction rate of 72 per cent.

Having developed profiling or predictive models in the Galway region, we then put these models to the test in the Waterford region. The Waterford data were not used in the development of the models. If the models developed in relation to the Galway sample can predict outcomes for the Waterford sample then we can have confidence in their wider applicability. The Waterford models were encouraging although the overall rate of correct prediction was lower than in Galway. The successful prediction rate was lower than in Galway (70 per cent) among men and somewhat higher (76 per cent) among women.

Implementing Profiling

The analyses in this report provide the basic information necessary to implement a profiling process among those on the Live Register and identify a list of specific characteristics which predict the probability that the person will remain on the Register long-term and ‘weights’ or coefficients for each of these characteristics. Working out the probability that a person will become long-term unemployed is a simple matter of adding together the coefficients for that person’s characteristics plus the ‘constant’ from the model and then transforming this from an ‘additive’ form to an ‘exponential’ form through exponentiation or ‘anti-logging’. However, this could be done more reliably and without special training if the official making the decision or processing the information from the customer is aided by computer software. This software could be as simple as a spreadsheet with some limited programming, or a more elaborate data base with a specific user interface, but neither would require a great deal of development and could be produced cheaply and

quickly, although consideration would have to be given to the training of specific staff in using the programme.

The report includes an attempt to quantify the potential reduction in unemployment that could be achieved by implementing a profiling system to identify early those most at risk of entering long-term unemployment combined with effective active labour market programmes to enhance the employment prospects of those so identified. The estimation combines information from the “Live Register Age by Duration Analysis” published by the CSO relating to October in each of the years 2000 to 2004, financial data on average expenditure on Live Register claimants, and on the results of previous evaluations of the impact of ALMPs in Ireland. We thus estimate that the annual saving to the exchequer could amount to almost €30 million in the first year of profiling, rising to a steady state of just over €60 million in the third and each subsequent year.

The report concludes by outlining the case for a national pilot of profiling to both increase the precision of the profiling models and to take account of regional or local differences in labour markets and in the processes governing the transition from unemployment to work.

1. DEVELOPING AND TESTING A PROFILING SYSTEM FOR IRELAND

1.1 Introduction

Research on the impact of active labour market programmes (ALMPs) suggests that such programmes should be well targeted to the needs of individual jobseekers and the labour market and that such interventions should start early in the unemployment spell. However, early interventions to assist in the labour market reintegration of individuals would be costly and potentially wasteful, since many new entrants to unemployment experience very short unemployment durations before becoming reemployed. This suggests the need to identify those individuals most in need of interventions and to deliver appropriate programmes to enhance their employment prospects. Profiling represents a systematic approach to the early identification of individuals with high risk of becoming long-term unemployed which entails both (i) formal methods for identification of individuals at risk of becoming long-term unemployed; and (ii) their referral to appropriate interventions.

The basic idea involved in profiling is to develop a statistical model of the effects of a range of factors on individual unemployment duration. By analysing a sample of individuals with varying unemployment durations it is possible to use statistical techniques to generate estimates of the effects of a range of characteristics on the probability that any individual will become long-term unemployed. The results of these models can then be applied by officials of the public employment service to assess the probability of any individual unemployed client becoming long-term unemployed. This can be achieved by combining the estimated coefficients from the statistical model with the personal characteristics of the individual client. Individuals can then be ranked in terms of their estimated probabilities of becoming long-term unemployed, and those with high probabilities can be referred for participation in ALMPs programmes.

Alternative approaches to selecting unemployed claimants for ALMPs include characteristic screening and interview-based allocation. Characteristic screening involves referring individuals to programmes if they have certain characteristics that are known to be associated with employability difficulties. So, for example, older

workers who have been unemployed for a long time are likely to experience difficulties in finding employment, so on this basis they might be referred for an ALMP. While this represents a clear and simple approach to identification and referral, it also has its limitations. If a restricted number of characteristics are used for screening, then some people with employability difficulties, but who do not display the target characteristic(s) may not be referred. If the number of target characteristics is extended, the likelihood of an individual who does not experience employability difficulties being referred for intervention increases, leading to wastage of resources. If the number of available places on ALMPs is limited, then characteristic screening provides little guidance for choosing between candidates for referral.

Interview-based identification entails an interaction between an official of the public employment service and an unemployed individual in which the official determines whether the client is in need of an ALMP on the basis of the interview and, possibly, administrative guidelines. This is essentially the approach adopted in Ireland under the National Employment Action Plan. The advantage of this approach is that it can be sensitive to the needs of each individual claimant, so incorrect judgements may be reduced. However, officials can still make incorrect judgements, and the approach is likely to increase the extent of variability in referrals, which can lead to unfairness in assignments, particularly when the number of places is limited. Research on the accuracy of an interviewer based system for allocating services to unemployed clients in Switzerland concluded that caseworkers achieved no better outcomes on behalf of their clients than would have been achieved by random assignment across available services (Lechner and Smith, 2003). Interview-based assessment is also costly and time-consuming for both unemployed clients and officials of the public employment service, so ideally, should be targeted to those most in need of such intervention.

The advantage of profiling over these alternative approaches to allocating active interventions is that it allows for a more systematic and rigorous identification of those who have a high probability of suffering from employability difficulties, who may become long-term unemployed, and who might benefit from ALMP interventions. Profiling has the additional advantage of allowing for the ranking of individuals according to their estimated probability of becoming long-term unemployed. Given scarce resources and limited numbers of places on programmes, such a ranking can be used to determine eligibility for ALMP referral. By selecting individuals with high probability scores, those most at risk can be assigned to programmes, and a cut-off point can be specified to determine eligibility. This allows administrators to control the numbers being referred to ALMPs and to ensure that those most in need of interventions are assigned places on programmes. Depending on resource availability, that cut-off point can be shifted to increase or reduce the absolute numbers of referrals from the top of the

ranking.

While profiling can lead to some individuals being assigned to programmes even though they may not need assistance, or to individuals not being referred who may be in need of assistance, the extent of incorrect assignments is likely to be lower using the profiling approach than either the characteristic or interview-based approaches. Errors in profiling derive from the limitations inherent in the regression models upon which profiling is based. Regression models entail estimating the best fit between a set of explanatory or predictor variables and an outcome variable (such as, for example, duration of unemployment, or long-term unemployment). Typically, regression models explain a limited percentage of the variation in an outcome variable, so some proportion remains random, or unexplained by the model. This necessarily gives rise to some incorrect predictions. However, the proportion of incorrect predictions generated from a systematic regression-based profiling system can be expected to be lower than in respect of either of the two alternative approaches. Moreover, once a profiling system is established it can be refined over time through further analysis.

An accurate profiling system, combined with effective labour market interventions, can reduce the unemployment duration of more disadvantaged unemployed by identifying them for early intervention and assistance with labour market integration or reintegration. As such, profiling has the potential to generate benefits both for the Department of Social and Family Affairs and for its unemployed customers. The principal benefits to the customer include more effective targeted services that can reduce unemployment duration and increase the probability of successful job acquisition. The principal benefits to the Department include increased effectiveness and efficiency of service delivery, and to the extent that a profiling system can lead to reduction in unemployment durations, to reduced expenditures on Unemployment Benefit and Unemployment Assistance. Additional potential benefits to the Department include the development of a system for prioritising client needs. Such prioritisation can provide objective and transparent criteria for resource allocation, allow for flexibility in service provision and resource availability, and also reduce potential wastage of resources from ‘creaming’ those more advantaged for labour market training interventions.

1.2 International Experiences of Profiling

Profiling has probably been most developed in the United States in the Worker Profiling and Reemployment Services (WPRS). Since 1993 States have been required by Federal legislation to establish profiling systems. WPRS consists of three elements: (1) Early identification of unemployment insurance claimants who are likely to exhaust their benefits; (2) Provision of reemployment services to those claimants identified as at risk; and (3) Collection of information on outcomes to check on continuing benefit eligibility

and to facilitate evaluations. Each state has to develop a statistical model that allows the employment service to predict the probability that a claimant will become long-term unemployed and/or exhaust their unemployment insurance benefits. The predictive models vary from state to state in terms of the variables included in the analysis, but generally include such factors as education, length of time in previous job, change in previous job/occupation and the local unemployment rate. Other personal characteristics such as age, gender, disability and ethnicity are not included in the models because of prevailing civil rights legislation. It is claimed, surprisingly, that the exclusion of these personal characteristics does not alter the results of the profiling models because of their association with the variables that are included in the model (OECD, 1998). Berger, Black and Smith (2000) argue that many existing profiling systems in the US generate poor predictions of the profiling variable and that this generally derives from a lack of predictor variables in the profiling models. Their evaluation of the Kentucky profiling model shows that it is possible to do a good job of predicting the profiling variables and show that the predictor variables are crucial for an effective profiling system. Eberts and O'Leary (2003), in their assessment of the profiling system in Michigan, and Black, Smith, Plesca and Shannon (2003) in their assessment of the Kentucky system, found that the predictive power of the model could be improved with inclusion of additional variables on previous wages and prior experience with unemployment insurance, and with the introduction of changes to the functional form of the prediction equation.

Profiling and referral to reemployment services are based exclusively on the results of the statistical model, and personal adviser discretion in the allocation of interventions to unemployed clients is explicitly prohibited. Jobseekers who are identified as at risk of exhausting their unemployment insurance benefits are obliged, at risk of losing their benefits, to participate in job-search assistance programmes. Where training slots are available profiled claimants can voluntarily participate in such programmes.

Berger, Black and Smith (2000) argue that the evaluation of profiling as an allocation mechanism and evaluating the impacts of the interventions or services being allocated by profiling are conceptually and practically distinct. This is significant because it draws our attention to the fact that it is important not just to identify those who are likely to experience difficulties in the labour market but also to deliver effective and appropriate interventions to enhance their employment prospects. Johnson (1996) found that States vary dramatically in the percentage of UI claimants referred to reemployment services (from less than 3 per cent to more than 75 per cent) and in the scope and intensity of reemployment services provided. States that used a more selective profiling strategy are generally more likely to provide more intensive reemployment interventions. The WPRS Evaluation Report found that about one-third of the States did not have the flexibility to change the number

of individuals referred to services based on need. So “areas with relatively low levels of dislocation served claimants with relatively low probabilities of exhaustion, while areas with larger dislocations served only those with the highest probabilities of exhaustion.” (Wandner and Messenger, 1999.) One strategy for increasing selectivity in service delivery is to establish a “threshold probability” – below which claimants would not be considered likely to exhaust their UI benefits and thus should not be referred to reemployment services.

A system of profiling was introduced in Australia in 1994 to identify adult jobseekers most at risk of becoming long-term unemployed. The profiling system uses the following predictors of long-term unemployment: age; educational attainment; Aboriginal and Torres Strait Islander status; birth in a non-English speaking country; English speaking ability; disability; and geographical location. In Australia the formal profiling system is complemented by assessments of public employment service officials, who can select jobseekers in the first 12 months of unemployment registration for further assessment on the basis of a set of supplementary factors. These additional factors include poor motivation, low self-esteem, poor numeracy and literacy skills and substantial time out of the workforce. In 1995, the formal profiling system identified about 5 per cent of screened applicants and a further 10 per cent were identified on the basis of the supplementary assessments. As such, the Australian system should be regarded as predominantly a characteristic screening rather than a profiling system. All those identified as at risk by either of the identification systems are interviewed and classified according to the likely difficulty in job placement. They are then required to wait for referral to case management but must participate once offered a place on a programme.

Under the UK Jobseeker Allowance system all unemployed workers are expected to be engaged in active job search. All labour market programmes, both active and passive, are designed to further this end, and the unemployment compensation system is operated in such a way as to keep the unemployed under constant pressure to seek work. Regular fortnightly interviews with clients are an important feature of the monitoring system, and reassessments at 13 and 26 weeks, and at 6-monthly intervals thereafter, are also undertaken, and these contacts can lead to referral for more intensive interventions, such as training or job search assistance, if they appear warranted.

The UK does not employ a formal profiling system, although extensive research on profiling has been conducted there. Payne, Casey, Payne and Connolly (1996) found that development of a profiling system for the UK was technically feasible although they expressed concern at the error rate in predictions of unemployment in the model developed in their study. A pilot project to evaluate a model to identify those at risk of remaining unemployed more than

12 months also concluded that the degree of error was unacceptable (Gibbins, 1997, Wells, 1998). However, a more recent study by Bryson and Kasparova (2003) based on a rich source of data generated as a part of the ONE service, a work-focused intervention to improve the quality and quantity of labour market participation of people of working age, is more optimistic about the potential for developing a profiling system for the UK. Bryson and Kasparova estimated separate models for three different client groups, including: job-seekers, lone parents, and people with disability; and for differing outcomes, including: probability of being out of work after 12 months, probability of claiming out-of-work benefits after 12 months, and percentage of time claiming out-of-work benefits over a 30 month period. They also examined the implications of using different sets of predictor variables. They concluded that it is possible to generate acceptable models predicting client outcomes; that separate models for different client groups are more accurate than single models for all clients combined, and that good quality data measuring a wide range of predictor variables enhances predictive power.

1.3 Policy Issues in Profiling

The key interest in profiling derives from its potential to deliver efficiency gains and financial savings both for unemployed individuals and for the State. From the point of view of the individual unemployed person, early identification and intervention of those most at risk of drifting into long-term unemployment carries obvious benefits, it should reduce the length of time an individual remains unemployed and accelerate his/her successful reintegration into the work force. From the point of view of the State, profiling has the potential to generate substantial savings by both targeting interventions only at those most in need and helping to reduce duration claiming unemployment benefits or assistance.

In order for these potential gains to be realised, it is essential not only that a profiling system accurately identifies those most at risk of experiencing employability difficulties, but also, that those identified are provided with effective interventions. Access to programmes depends on the capacity of the system. Research in the US found that the available number of places in job-search assistance programmes is often insufficient to cater for the number of claimants profiled as being at risk of exhausting their benefits. Only about one-third of all claimants profiled and subsequently placed in the “selection pool” gets referred to reemployment services (Wandner and Messenger, 1999).

In the Irish case a preventive intervention system to minimise the inflow to long-term unemployment has been in operation for a number of years. Under the National Employment Action Plan (NEAP), developed in response to the European Employment Strategy. In the preventive strategy implemented under the NEAP, unemployed people are referred by the Department of Social and Family Affairs for interview by FÁS as they cross specified

unemployment-duration thresholds on the Live Register. The interview aims to initiate a process leading to the offer of a job or placement in an education or training programme with a view to enhancing the employability of the client. The process commenced in September 1998 with all those under 25 years of age who were six months on the Live Register were referred for interview. Over time the process has been progressively expanded to include additional groups crossing specified thresholds of unemployment duration. The process of “full engagement” with all unemployed people (both stocks and flows) was introduced on a pilot basis in two regions, Galway and Clondalkin in 2001, and the process of full engagement was extended to all areas in 2003. All those aged under 55 years are referred when they cross the 6 month threshold.

Ireland’s *National Employment Action Plan, 2004* reports that of almost 45,000 clients interviewed by FÁS between January 2003 and July 2004, 6,447 were recorded as being in employment. A further 3,168 had entered a FÁS training programme, and 1,593 had entered other education or training programmes. An additional 10,655 of those interviewed had left the Live Register without notification of destination. The remaining interviewees had either been referred to a programme place but were still on the Live Register or were receiving ongoing support. (Department of Enterprise, Trade and Employment, 2004).

Implementation of a profiling system may have important implications for both the capacity and the nature of ALMP provision. Under the current policy regime most new entrants to unemployment (i.e. those aged under 54 years) are referred through the NEAP process when they cross the 6-month threshold. Introduction of a profiling system would entail substantial changes to this process since it would (1) identify, early in the unemployment spell, those most at risk of experiencing employability difficulties (presumably at or shortly after first registration; and (2) refer them for early ALMP interventions. A substantial proportion of new entrants to unemployment find jobs and exit the Live Register before 6 months have elapsed. The present policy regime effectively allows this natural exit process to unfold and intervenes with those who remain on the register after 6 months. A profiling system would eliminate this “waiting period” to discover who is at risk of long-term unemployment, and would accelerate the delivery of interventions to those identified as most at risk, and, assuming effective intervention, shorten their duration out of the workforce. Profiling would also increase the likelihood that interventions become targeted at those most in need. This would entail a shift in the demand profile for interventions, with increased delivery early in unemployment spells and a reduction in interventions at later stages (i.e. after 6 months and beyond). Provision of ALMPs in response to a profiling system could also entail some changes in the nature of programmes being offered if profiling were to result in a change in the composition of ALMP participants and in their needs.

At end 2003, there were a total of 67,201 persons on ALMPs in Ireland (DETE, 2004). This can be compared with a total of 85,900 individuals unemployed in the fourth quarter of 2003. Thus, there is substantial capacity in ALMP provision. Implementation of profiling would however, entail some shift in the balance of provision from long- to short-term unemployed. It would also be essential that interventions provided to individuals identified in a profiling system be effective. Previous research in Ireland has shown that ALMPs with strong linkages to the labour market, both training and subsidised employment, are more likely to enhance the employment prospects of their participants and the lessons learned from these evaluations could well be applied in developing ALMP provision to cater for profiled clients (Denny, Harmon and O'Connell, 2000; O'Connell, 2002). It should be noted that the numbers on Community Employment (CE) have been reduced in recent years. CE is mainly, but not exclusively, targeted on the long-term unemployed and others with particularly severe labour market disadvantages. However, it has weak linkages to the market and has been shown to have limited impact on employment prospects (O'Connell, 2002). Resources freed up from the contraction of Community Employment could be employed to provide effective ALMPs to assist profiled clients.

1.4 The Structure of this Report

The key to profiling is to develop a reliable statistical model that explains or predicts the duration of individual unemployment spells with some precision on the basis of information on a range of personal characteristics that can be reasonably easily collected at the beginning of an unemployment spell. Our objective in the present study is to identify the key personal characteristics that influence the probability that any new entrant to unemployment will become long-term unemployed.¹ Having identified those key characteristics we then develop a model to estimate the size of the effect of each variable on the probability of an individual becoming long-term unemployed. The parameters or coefficients generated by that model can then become the predictive tools to be used by officials of the Department of Family and Social Affairs in profiling their customers.

Under current procedures, the Department of Family and Social Affairs collects information on a limited set of personal characteristics when an individual first registers. In this study we supplement the standard administrative data recorded in the Live Register with a range of individual level data collected in a series of surveys collected by the DSFA in Galway and Waterford. The results

¹ The ultimate objective of developing a profiling system is to allow prediction, at the time that an individual first becomes unemployed, their likely employment situation after 6 and 12 months. Such prediction is not feasible on the basis of information currently available, but successful piloting of a profiling system for Ireland could generate such predictability.

of these surveys are described in Chapter 2. Use of this data provides us with a wider range of variables that may influence unemployment duration. We also have access to administrative records from the Live Register relating to claimant patterns over a three-year period, and we analyse duration on the Live Register using this data in Chapter 3. By matching the survey data with administrative records from the Live Register, we are then able to examine the factors that influence duration on the Live Register. Chapter 4 presents an analysis of the general factors that influence the duration of spells on the Live Register and exit to one of three alternative destinations: employment, a Community Employment scheme, or some other destination (including retirement, home duties, or other form of withdrawal for the labour market).

Having generated a general understanding of the factors that determine whether and when an unemployed individual will leave the Live Register, we then focus in Chapter 5 on the development of a formal profiling model of the probability that any individual be on the Live Register for a period of 12 months or more.

2. A COMPARISON OF THE GALWAY AND WATERFORD SAMPLES OF UNEMPLOYED

2.1 Introduction

This study is based upon data on unemployed individuals from Galway and Waterford Regions from two different sources: surveys of the unemployed in each region and administrative information drawn from the Live Register of the Unemployed of the Department of Social and Family Affairs. The survey data come from three surveys, one in each region carried out in the year 2000 and a third, or ‘follow-up’ sample, carried out among the original Galway sample in late 2002. Information from the Live Register for the respondents sampled in the first surveys was then collected and combined with the original data so that analyses of duration on the Register could be performed. In this chapter we briefly outline the structure of the data available from these different sources before comparing the sample of unemployed people in the Galway and Waterford regions. There are a number of characteristics of individuals that can influence their prospects of making the transition from unemployment to work. Chief among these are age, gender, education, duration of unemployment, previous labour market experience, and participation in education, training or employment schemes for the unemployed. It is useful, therefore, to compare Galway and Waterford in terms of how these variables are distributed among the unemployed in both cities and environs. Once we have established the nature of the sample in this chapter we will be in a better position to begin the analysis of the factors related to duration on the Register in subsequent chapters.

2.2 The Galway and Waterford Samples of the Unemployed

In May/June 2000 the Galway Regional Office of the Department of Social and Family Affairs selected and interviewed 1,434 people on their Live Register in a study of unemployed customers and employment opportunities (Kennedy *et al.*, 2001). The long-term unemployed (12 months+) were over sampled within this 1,434 people, so that more in-depth analyses could be carried out on this group, thus the attained Galway sample (i.e. the actual sample

interviewed) was approximately 75 per cent long-term unemployed. In the Waterford Region, an identical sampling and interview process was carried out in October/November of 2000 yielding 1,374 respondents, around 75 per cent of whom were also long-term unemployed (see Maher *et al.*, 2001). From the Autumn of 2002 through to the Spring of 2003, the Galway Regional Office attempted to re-interview the 1,434 respondents originally interviewed in 2000 and were relatively successful in this, managing to interview 1,083 of the original respondents. This survey is referred to as the 'Follow-up' Survey and we will be using data from this in the next chapter to compare the pictures of durations of unemployment presented by Register and survey data.

Table 2.1 shows the Galway and Waterford samples by duration of unemployment. In both cities the design of the surveys entailed an over-sampling of the long-term unemployed, in order to ensure adequate numbers for analysis of this group. Panel B shows the results of re-weighting the sample using regional data on unemployment by duration and gender published by the Central Statistics Office (2000) relating to Galway in April 2000 and Waterford in October 2000. The re-weighted data show that the incidence of long-term unemployment in total unemployment was somewhat higher in Galway (42 per cent) than in Waterford (38 per cent). The national rate of long-term unemployment, relative to total unemployment in the state, was 39 per cent in both May and October 2000, when the fieldwork for the surveys in both regions was carried out. So the rate of long-term unemployment in Galway was slightly higher than the national average, while the rate in Waterford was slightly lower.

Table 2.1: Galway and Waterford Samples, by Duration of Unemployment

	Short-term Unemployed (< 1 year) %	Long-term Unemployed (> 1 year) %	N of Cases
Unweighted sample			
Galway	25.7	74.3	1,434
Waterford	25.4	74.6	1,374
Weighted Sample			
Galway	58.4	41.6	1,434
Waterford	62.5	37.5	1,374

The age structure of unemployment in both regions is quite similar, with about three-quarters of the total unemployed between the ages of 25-54 years (Table 2.2). In both cities, also, the age distribution among the short-term unemployed is skewed toward the younger age groups, while that of the long-term unemployed is skewed toward the older age groups. This is particularly prevalent in Galway, where over 50 per cent of the short-term unemployed are aged between 18-34, while almost 50 per cent of the long-term unemployed are aged between 45 and 66 years. Short-term

unemployment in Galway also displays a younger age distribution than in Waterford.

Table 2.2: Unemployment by Age-group and Duration

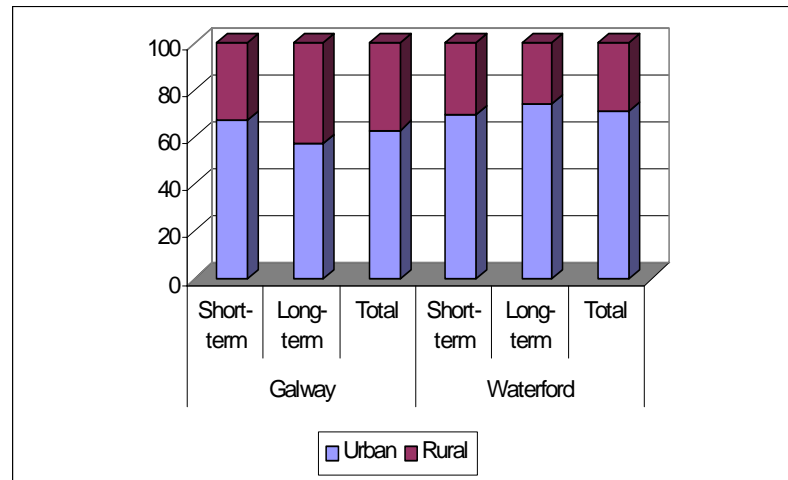
Years	Galway			Waterford		
	Short term %	Long term %	Total %	Short term %	Long term %	Total %
18-24	20.9	5.5	14.5	15.4	9.9	13.3
25-34	32.8	16.8	26.2	28.2	19.2	24.8
35-44	24.5	28.2	26.0	25.3	24.3	24.9
45-54	12.6	35.6	22.2	16.3	32.6	22.4
55-66	9.2	13.8	11.1	14.8	14.0	14.5
	100.0	100.0	100.0	100.0	100.0	100.0

In general, men account for a larger share of the unemployed. In Galway, 59 per cent of the unemployed were men, while in Waterford 54 per cent were men. This gender difference is more pronounced among the long-term unemployed: 65 per cent of the long-term unemployed in Galway, and 61 per cent in Waterford, were men.

Table 2.3: Unemployment by Gender and Duration

	Galway			Waterford		
	Short term %	Long term %	Total %	Short term %	Long term %	Total %
Men	54.3	65.3	58.9	49.6	61.4	54.0
Women	45.7	34.7	41.1	50.4	38.6	46.0
	100.0	100.0	100.0	100.0	100.0	100.0

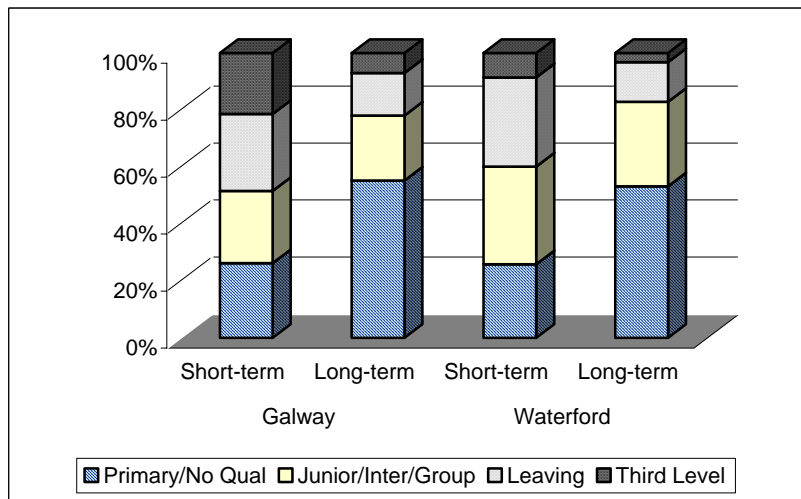
Residential location can influence labour market prospects because of local labour market conditions. Figure 2.1 shows urban-rural residence of the unemployed in the two regions. A greater proportion of the unemployed in Waterford (71 per cent) lived in urban locations than in Galway (63 per cent). In fact, the underlying difference mainly relates to the long-term unemployed: in Galway only 57 per cent of the long-term unemployed were urban residents, compared to almost three-quarters of the long-term unemployed in Waterford.

Figure 2.1: Urban-Rural Residence by Unemployment Duration

2.3 Education and Training

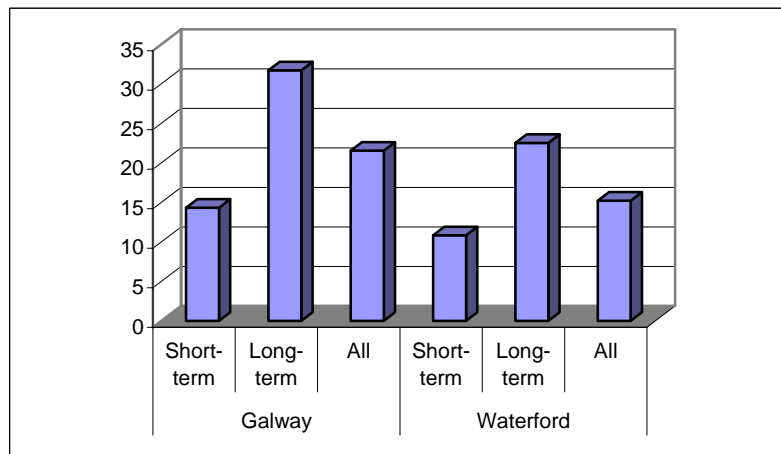
Most, if not all, analyses of the relationship between education and unemployment in Ireland have shown that those with lower levels of educational attainment have higher risks of long-term unemployment. This is reflected in Figure 2.2, which shows the distribution of educational attainment by unemployment duration in the two cities. In both, the distribution of educational attainment among the long-term unemployed is substantially less favourable than among the short-term unemployed. More than half of the long-term unemployed in both Galway and Waterford had, at best, a Primary Certificate level of education, compared to less than a quarter of the short-term unemployed. Three-quarters or more of the long-term unemployed in both regions had a Junior Certificate level of education, or less, compared to 47 per cent of the short-term unemployed in Galway, and 56 per cent of the short-term unemployed in Waterford. At the other end of the educational spectrum, a substantially larger proportion of the short-term unemployed had attained the Leaving Certificate or attended third level education. Galway, however, has higher rates of attainment of third level qualifications, perhaps reflecting its status as a university city. Almost 20 per cent of the short-term unemployed, and 7 per cent of the long-term unemployed had attended third level education, compared to 8 per cent and 3 per cent in Waterford.

Figure 2.2: Educational Attainment by Unemployment Duration



While Galway displays higher rates of third level education, it is also characterised by higher rates of reported problems with literacy and numeracy among the unemployed. Overall, 21 per cent of the unemployed in Galway, and 15 per cent in Waterford, reported that they had ‘problems with reading, writing and figures’.

Figure 2.3: Reported Problems with Literacy and Numeracy by Unemployment Duration



Literacy and numeracy problems were particularly prevalent among the long-term unemployed: almost 32 per cent of the long-term unemployed in Galway reported such problems, as did 23 per cent of the long-term unemployed in Waterford. Participation in temporary education or training programmes may improve individual employment prospects. Respondents were asked whether they had attended each of a list of education and training programmes over the previous three years and the results are shown

in Table 2.4. Accordingly, we cannot aggregate across the different programmes, because some individuals may have engaged in more than one form of education or training.² In general, both cities are similar in terms of participation rates in continuing education and training. In both cities, participation in evening and other part-time adult education courses was the most common form of continuing education or training, just over 12 per cent of the unemployed participated in such courses. This was followed by FÁS courses: about 7 per cent of the unemployed in each city had participated in FÁS courses over the previous three years.

Table 2.4: Participation in Education or Training Programmes in the Past 3 Years

	Galway			Waterford		
	Short term	Long term	Total	Short term	Long term	Total
	%	%	%	%	%	%
FÁS Course	9.8	3.0	7.0	8.0	5.4	7.1
CERT Course	0.8	0.3	0.6	0.8	1.0	0.9
Vocational Training						
Opportunity Scheme	3.5	1.0	2.4	1.4	3.1	2.0
Back to Education Allowance	0.8	0.8	0.8	1.4	0.4	1.0
Evening Course	17.3	6.5	12.8	14.7	7.8	12.1
Other	2.4	1.3	2.0	2.6	2.1	2.4

The table also reveals important differences between the two cities when we consider rates of participation by unemployment duration. In Galway, the discrepancies in participation rates between the short- and the long-term unemployed are marked, and greater than in Waterford. For example, 17 per cent of the short-term unemployed participated in evening or other part-time education courses in Galway, compared to only 6.5 per cent of the long-term unemployed. The corresponding rates in Waterford were 15 per cent and 8 per cent respectively. So the short-term unemployed in Galway were more likely than their counterparts in Waterford to participate in continuing training, while the reverse was true in relation to the long-term unemployed. This may point to differences in the two cities in access to continuing education and training opportunities that act to the disadvantage of the long-term unemployed in Galway.

Table 2.5 shows that a slightly higher proportion of the unemployed had ever participated in the Community Employment Scheme, its predecessor, the Social Employment Scheme, or a FÁS

² In fact, further analysis indicated that multiple participation in different courses was rare.

Jobs Initiative in Galway than in Waterford.³ This reflects the fact that in Galway similar proportions of the short-and long-term unemployed (just over 16 per cent) had ever participated in such schemes. In Waterford, 13 per cent of the short-term unemployed, and 17 per cent of the long-term unemployed had participated.

Table 2.5: Ever Participated in a Community Employment Scheme

	Short term	Long term	Total
	%	%	%
Galway	16.6	16.4	16.5
Waterford	13.1	17.1	14.6

2.4 Labour Market History

Individual labour market prospects are strongly influenced by their previous labour market history. Table 2.6 looks at the number of jobs held before the current spell of unemployment. The two cities differ in terms of the two extremes of the distribution. In Galway a higher proportion had never worked than in Waterford (7 per cent versus 5 per cent) and a greater proportion had had more than 10 jobs (17 per cent versus 11 per cent), a number of jobs which suggests a highly unstable work history. As might be expected, in both cities, the long-term unemployed were more likely than the short-term unemployed to have never had a job, or to have had 10 or more jobs. In this latter respect, Galway stands out: almost 20 per cent of the long-term unemployed had had more than 10 jobs, compared to 11 per cent in Waterford.

Table 2.6: Number of Jobs Held Prior to Current Unemployment Spell

	Galway			Waterford		
	Short term	Long term	Total	Short term	Long term	Total
	%	%	%	%	%	%
None	4.2	10.7	6.9	4.0	7.6	5.3
1 or 2	23.7	25.8	24.6	25.9	28.2	26.7
3 to 5	35.1	27.6	32.0	37.9	33.7	36.3
6 to 10	21.2	16.7	19.3	21.9	19.1	20.9
10+	15.9	19.3	17.3	10.2	11.5	10.7
	100.0	100.0	100.0	100.0	100.0	100.0

Interesting differences emerge between the two regions in the duration of the last job held, for those who had previous work experience shown in Table 2.7. A substantially greater proportion of the unemployed in Waterford had held their previous job for 5 years or more (33 per cent) than in Galway (19 per cent), and this was true irrespective of the duration of the current spell of unemployment.

³ Note that the question referred to participation at any point in time, so there is no necessary relationship between the duration of the current unemployment spell and participation in such schemes.

Table 2.7: Duration of Tenure in Last Job, by Current Duration of Unemployment

	Galway			Waterford		
	Short term	Long term	Total	Short term	Long term	Total
<Month	5.1	4.9	5.0	3.0	4.9	3.7
1 to 6 Months	34.3	21.3	29.2	23.6	20.4	22.4
6-12 Months	17.5	19.0	18.1	16.1	16.1	16.1
1 to 5 Years	26.7	30.8	28.3	23.4	26.3	24.4
>5 Years	16.4	24.0	19.4	33.9	32.3	33.3
	100.0	100.0	100.0	100.0	100.0	100.0

These regional differences in previous job tenure may be related to the nature of demand in the local labour market. Table 2.8 shows that the proportion of the unemployed in the production industries sector was substantially higher in Waterford (28 per cent) than in Galway (15 per cent) – a difference that cuts across the distinction between short- versus long-term unemployment. In Galway, there were higher proportions in construction and other services; sectors characterised by higher rates of labour turnover than in manufacturing industry.

Table 2.8: Economic Sector of Last Job, by Current Duration of Unemployment

	Galway			Waterford		
	Short term	Long term	Total	Short term	Long term	Total
	%	%	%	%	%	%
Agric., Forestry & Fishing	3.7	5.4	4.4	4.6	8.6	6.1
Other Product Industry	15.0	14.9	15.0	30.0	24.1	27.8
Construction	12.2	22.8	16.6	10.2	13.4	11.4
Wholesale & Retail	14.4	8.2	11.8	11.3	10.3	10.9
Hotels and Restaurants	10.7	6.4	8.9	9.2	7.0	8.4
Transport & Communications	2.9	3.7	3.2	7.7	4.9	6.6
Finance & Business Services	3.7	2.5	3.2	2.6	2.7	2.6
Public Admin. & Defence	3.0	2.2	2.6	1.2	2.5	1.7
Education & Health	10.6	5.5	8.5	6.1	3.7	5.2
Other Services	18.1	18.3	18.2	13.8	15.4	14.4
	100.0	100.0	100.0	100.0	100.0	100.0

2.5 Job Search

We expect that employment prospects will be related to the frequency and intensity of job searching, although the causality here is not entirely clear-cut, since those who realise that they have very poor prospects of finding work may search for work less intensely, if at all. Table 2.9, showing when respondents last applied for a job, suggests no marked regional differences in the frequency of job search. However, there is a clear difference between the short and the long-term unemployed, with the short-term unemployed far more likely to have applied for a job in the past month than the long-term unemployed.

Table 2.9: When Last Applied for a Job

	Galway			Waterford		
	Short term	Long term	Total	Short term	Long term	Total
	%	%	%	%	%	%
Past week	27.4	7.6	19.1	20.5	8.6	16.0
Past 2 weeks	13.0	6.4	10.3	14.6	6.8	11.7
Past month	22.0	14.1	18.7	21.3	12.5	18.0
Past year	20.9	29.7	24.6	21.4	25.0	22.8
Over 1 year	13.0	34.8	22.1	17.0	38.1	25.0
Never	3.7	7.4	5.2	5.2	9.0	6.7
	100.0	100.0	100.0	100.0	100.0	100.0

This difference is particularly marked in Galway, where 40 per cent of the short-term unemployed had applied for a job in the past two weeks, compared to only 14 per cent of the long-term unemployed.

The unemployed in Galway do seem to have searched somewhat more intensely for work, however, as shown by Table 2.10. The mean number of job applications over the previous 12 months was 2.5 in Galway, compared to 2.2 in Waterford, and almost 15 per cent of the Galway sample had made more than 15 job applications, compared to only 8.5 per cent in Waterford. Moreover, 28 per cent of those in Galway, compared to 34 per cent in Waterford, had not applied for any job in the past 12 months.

Table 2.10: Number of Jobs Applied for in Past 12 months

	Galway			Waterford		
	Short term	Long term	Total	Short term	Long term	Total
	%	%	%	%	%	%
None	17.5	42.3	27.8	25.6	48.3	34.1
1 to 5	29.2	29.0	29.1	40.4	27.1	35.4
5 to 10	22.2	13.1	18.4	16.3	12.5	14.9
10 to 15	12.8	5.9	9.9	8.0	5.7	7.1
Over 15	18.3	9.7	14.7	9.7	6.4	8.5
	100.0	100.0	100.0	100.0	100.0	100.0
Mean	2.9	2.1	2.5	2.4	1.9	2.2

‘Word of mouth’ and personal contact was identified as the most common way that respondents heard about the last job that they applied for in both regions (see Table 2.11).

2.6 Looking for Work

Figure 2.4 shows the proportion of the unemployed in each region who believed that they would get a job within the next three months.

Overall, the Waterford sample is a little less optimistic than the Galway sample: 55 per cent in Galway believed they would get a job in the next three months, compared to 51 per cent in Waterford. This difference is entirely due to differences among the short-term unemployed, 70 per cent of whom in Galway, but only 61 per cent of whom in Waterford, believed they would get a job in three months. Only about one-third of the long-term unemployed in both regions believed they would get a job within this timeframe.

Figure 2.4: Proportion Who Believe They Will Get a Job in Next 3 Months

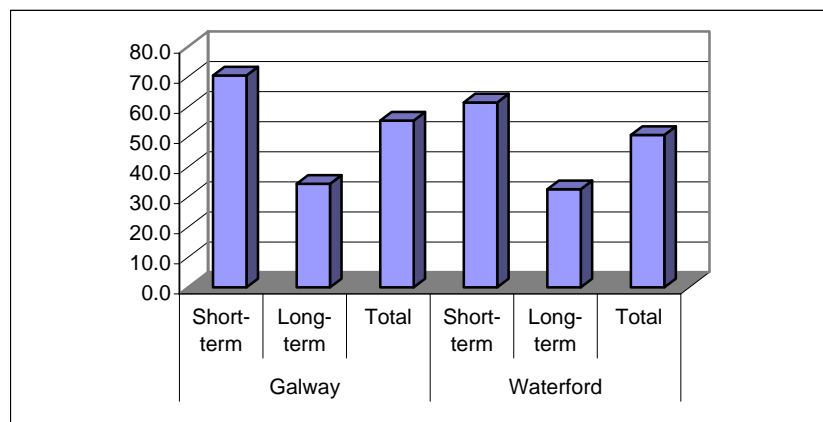


Table 2.13 shows how far respondents would be willing to travel to work. The unemployed in Waterford seemed to be prepared to travel further than those in Galway. About 60 per cent of the unemployed in Galway responded that they would be willing to travel to work within the town or city, or a distance of up to 5 miles, compared with 50 per cent of the Waterford sample. Only 10 per cent of the Galway sample, and 14 per cent of those in Waterford, indicated that they would travel more than 30 miles to work. In both regions, the long-term unemployed were less mobile than their short-term unemployed counterparts.

These differences in preparedness to travel to work may be related to availability of transport: almost half the unemployed in Waterford owned a car, compared to less than a third of those in Galway, and those in Waterford were somewhat more likely than those in Galway to be living near to a main bus route (see Table 2.14). As might be expected, car ownership was more common among the short-term unemployed in both regions.

Table 2.13: How Far Would Respondent Travel to Work?

	Galway			Waterford		
	Short term %	Long term %	Total %	Short term %	Long term %	Total %
Within city/town or under 5 miles	55.1	65.7	59.4	44.3	60.3	50.2
Up to 10 miles	16.1	14.1	15.3	22.5	19.0	21.2
Up to 20 miles	11.1	10.4	10.8	13.4	7.0	11.1
Up to 30 miles	4.7	3.2	4.1	3.9	1.9	3.2
Over 30 miles	13.0	6.6	10.4	15.9	11.7	14.4
	100.0	100.0	100.0	100.0	100.0	100.0

There were substantial differences between the regions in the proportions willing to consider moving to take a job: 30 per cent in Galway, but only 21 per cent in Waterford would consider moving to take a job. This difference is mainly due to differences between the short-term unemployed in the two regions: in Galway 38 per cent of the short-term unemployed would consider moving, compared to only 24 per cent in Waterford.

Table 2.14: Transport Factors in Job Search

	Galway			Waterford		
	Short term %	Long term %	Total %	Short term %	Long term %	Total %
Own a car	35.0	27.2	31.7	55.7	31.1	46.5
Full Driving Licence	43.9	40.3	42.4	51.2	36.7	45.8
Main bus route	74.1	62.8	69.4	71.2	74.8	72.6
Consider moving	38.2	18.6	30.1	23.6	16.7	21.0

About two-thirds or more of the unemployed in each region were registered with FÁS, and the highest registration rate was among the short-term unemployed in Waterford, where almost three-quarters were registered with FÁS (Table 2.15). Registration with private employment agencies was also quite common, and more so in Galway, where almost 20 per cent of all unemployed, and 26 per cent of the short-term unemployed were registered with private agencies. Registration with CERT and with the Local Employment Service (LES) was comparatively rare across the two regions.

Table 2.15: Whether Registered with the Following

	Galway			Waterford		
	Short term %	Long term %	Total %	Short term %	Long term %	Total %
FÁS	63.4	63.3	63.3	72.2	66.2	69.9
CERT	1.1	1.8	1.4	2.3	1.4	2.0
Private Agency	25.8	10.4	19.4	16.1	5.0	11.9
Local Employment Service	5.7	4.7	5.3	7.2	6.0	6.8
Other	3.1	3.3	3.2	4.4	1.8	3.3

2.7 Summary and Conclusions

Our comparison of the samples of the unemployed in Galway and Waterford has focused on individual factors which may influence labour market prospects. We found that the incidence of long-term unemployment in total unemployment is somewhat higher than the national average in Galway and somewhat lower in Waterford. Unemployment duration is important, not only because there are important differences in the composition of the long- versus the short-term unemployed, so that, for instance, the short-term unemployed generally show a more favourable distribution of education and skills, but also because unemployment duration itself has a strong influence on individual chances of escaping unemployment to work. In most instances, the two regions are very similar in the distribution of factors that can influence employment prospects, and the main differences are much more strongly related to unemployment duration than to region.

We found that the age and gender distributions of the two samples are very similar, but that a greater proportion of the Waterford sample is urban resident, particularly among the long-term unemployed. The unemployed in the Galway sample display a more favourable distribution of educational attainment than in Waterford, but Galway is also characterised by higher incidence of problems with literacy and numeracy, particularly among the long-term unemployed.

Previous labour market experiences may have been less advantageous in Galway: a greater proportion of the unemployed in Galway had either never worked or had held more than 10 jobs in their careers, the latter suggesting a highly unstable work history. Moreover, those in Galway who had held jobs prior to the current unemployment spell were more likely to have held that job for a shorter duration than their Waterford counterparts. The unemployed in Waterford were more likely to have worked in the production industries sector in their last job, while in Galway there were higher proportions in construction and services.

There was little difference between the two regions in the frequency of job searching, but the unemployed in Galway do appear to have searched more intensely than those in Waterford. There were also some differences in job-search methods, with the unemployed in Waterford more likely to use print and electronic media information sources. The unemployed in Galway were a little more optimistic about their job prospects than those in Waterford, and this was due to greater confidence among the short-term unemployed in Galway that they would find a job within the next 3 months.

The unemployed in Waterford appeared willing to travel further to work than their Galway counterparts, a difference which may have been due to higher rates of car ownership in Waterford, and to the fact that a higher proportion of those in Waterford lived close to a main bus route.

3. THE DISTRIBUTION OF UNEMPLOYMENT DURATIONS

3.1 Introduction

In this chapter we extend the simple analyses of the last by moving to a more refined measure of time spent on the Live Register. Up to this point we have been talking largely of two broad groups called the long and short-term unemployed. Though we discuss these groups as if they are wholly separate populations, in reality they are, of course, just simplifications of a more complicated situation in which individuals with certain characteristics leave unemployment earlier leaving those with more disadvantageous characteristics in unemployment for longer. Over time the proportions of those with different characteristics comes to reflect these processes and we end up with the descriptive picture laid out in the previous chapter. Yet the duration of an *unemployment spell* as opposed to a *cross-sectional* picture of those unemployed at a single point in time, is crucial for understanding both the processes at work and the impact of unemployment on the person. Although unemployment will be rarely welcomed, short spells will have little impact on the individual and their family and may even give the person time to find a more suitable job which will be more stable and perhaps more rewarding in the future. A long spell of unemployment on the other hand, will often have severe financial consequences for both the individual and family as well as impacting on psychological well-being and social life.

In our data, we are in the fortunate position of having information on the duration of unemployment from two different sources: from the Follow-up Survey carried out in Galway in the period after Autumn 2002 and the Register data for both the Galway and Waterford Regions. In the first section in this chapter we will compare the pattern of durations found using the two sources and discuss the implications that this has for our understanding of the register data before moving on to an in-depth examination of the durations derived from the register data alone in the second section.

3.2 Comparing Survey and Register Durations

To calculate the duration of a spell of unemployment we first need to know when the person became unemployed. Luckily both the Register and Follow-up data use the same date as found in the Register data (used to select the original sample). Although it would seem simple to derive a beginning date, this is actually rather more complicated to derive than would be expected since the start of an unemployment spell can be both the commencement date of this claim and the cumulative total time spent on the register in total, if previous spells have been sufficiently close together in time and certain administrative choices have been made. The latter measure is used for national statistics on length of unemployment where the division between short- and long-term is made. Here however we choose to use the commencement date as, though not necessarily better, this date does give us a stable starting date.

Although the survey and register information collected as part of this project nominally refer to the same event (i.e. a spell of unemployment which was ongoing in May/June of 2000) it is possible that the information derived from the two sources will not be identical. Several factors could intervene to make the measured durations of unemployment from these two sources differ. These differences are important since they not only refer to the duration of the spell itself, but also to the outcome of the spell, i.e. whether someone leaves unemployment, whether the observation of the spell is ‘censored’ by the end of the observation period and the destination to which they leave. Differences in these three dimensions – duration, whether censored and destination can critically influence the patterns observed and the conclusions drawn about the processes at work. It should be remembered that the Register is an administrative tool rather than a perfect record of activity status and this is reflected in the manner in which the information it holds is organised.

In defining the duration of the unemployment spell and the destination if the person left, we take the first break that occurs, even if that person later became unemployed again. This categorisation is however made in different ways for the Register and Follow-up Surveys. In the Register we take the first event after the commencement date of the spell, which can also include an automatic definition as having left the Register if the person has not reregistered that month. This group are listed separately in the following analyses. The Follow-up Survey information allows us to perform a similar procedure, but also allows us to track changes in status that do not emerge from Register data such as when Live Register customers redefine themselves as caring for household members and children or as retired rather than as searching for work.

Looking first at differences in the extent of censoring and destinations reached, Table 3.1 shows the proportion of each destination category in the Register data by Follow-up Survey outcome.

Table 3.1: Cross Tabulation of Destinations from the Register and Follow-up Survey Information (Unweighted)

Register Destination	Follow-up Survey Destination							Total %	N
	Censored	Employed	CE	Ret.	Training	Inactive	Other		
Censored	53.1	16.4	0.8	4.8	3.4	20.1	1.3	100	621
Employed	15.4	65.8	0.0	0.9	6.8	9.4	1.7	100	117
Disappeared	38.5	26.0	0.0	4.8	5.8	24.0	1.0	100	104
Community Employment	21.0	37.0	13.6	0.0	16.0	9.9	2.5	100	81
Retired	50.0	1.6	0.0	30.6	3.2	12.9	1.6	100	62
Training	39.1	17.4	0.0	4.3	30.4	4.3	4.3	100	23
Inactive	40.0	10.0	0.0	0.0	3.3	43.3	3.3	100	30
Other	46.7	13.3	0.0	0.0	6.7	33.3	0.0	100	15
Number	464	246	16.0	56	59	196	16	100	105

Of those cases who are defined as not having left unemployment on the Register data (the ‘censored’ in the top row), just over half have remained unemployed in the Follow-up Survey results, although a further 30 per cent have exited to categories that may well allow them to remain on the register such as being a full-time domestic worker (which is combined with being ill/disabled in ‘inactive’), being in training or education or seeing themselves as retired. However, 16 per cent of those who remain unemployed reported that they become employed in the Follow-up Survey which raises questions about eligibility of these clients to unemployment benefits or assistance, although it is possible that these people were working part-time and were thus eligible for benefits.

Approximately two-thirds of those who reported to the DSFA that they were employed also reported this in the Follow-up Survey, although a substantial 15 per cent also reported that they remained unemployed which may suggest that these people had short term jobs (which here must be less than a month) and then returned to unemployment. The third row of Table 3.1 gives the proportion who ‘disappeared’ from the Register by Follow-up Survey category. This shows that this group were split roughly three ways: one-quarter going to employment, one-quarter becoming inactive and a further two-fifths remaining unemployed (but not in contact with DSFA).

Although only 14 per cent of those who move onto a Community Employment Scheme from the Register do so in the Follow-up data, a further 37 per cent state that they became employed and 16 per cent that they entered training. A further fifth of this group stated that they remained unemployed.

Perhaps the clearest join between the two data sources is for the retired where over 80 per cent state that they are retired or remain unemployed. The latter is understandable given that this group is made up of those moving onto Pre-Retirement Allowance and allied

schemes. A similarly clear picture emerges for those who became 'inactive' in the Register, i.e. who were not gainfully seeking work or who had moved onto Disability allowance. Two-fifths of this group regard themselves as still unemployed in the Follow-up Survey and a further two-fifths define themselves as inactive.

These results suggest that although the alignment between the data sources is by no means perfect, it is relatively high with roughly 50 per cent of destinations being matched between the two sources and a further 28 per cent of the total in non-matching cells which can be easily explained. It is difficult to fully explain the remaining 22 per cent, but it is possible that reporting error in the Register may be combined with poor recollection in the Follow-up Survey.

Although the destinations from the two sources are quite close, to what extent is this true of the durations observed? There are several factors that may lead the Register period to be longer than the self-reported duration. First of all, although updated regularly, it is possible that the gap between a customer informing the Department of their new status and the records themselves being updated can lead to some drift between the measures, although this should be no more than a month given standard practices. On the other hand, a bigger gap may appear if the customer simply fails to return to the Department and updating only occurs as part of the automatic 'clearing' operations of the register. It is also possible of course that differences between the survey data and the Register can occur because respondents actually begin working, but continue to claim social welfare benefits.

However, it is also possible that the self-reported durations in the Follow-up Survey will be longer. Movements off the Register, such as to Community Employment Schemes, moves to other benefits such as PRETA and Disability Benefit and having benefits stopped because the customer is not actively seeking work all appear as exits to the Register, but the people themselves (as we have seen above) may still regard themselves as unemployed. Given these different possibilities we should compare the durations from the different sources. One way to do this is to directly compare the two sources and express the difference between the two as a proportion of the Register duration. If we do this we find that the match is actually very close with 70 per cent of all cases having Register and Follow-up durations within 10 per cent of each other. Moreover, if we exclude the cases which were censored (i.e. had not ended by the time the data were harvested) then agreement increases with 80 per cent of cases having durations within 10 per cent of each other. This translates into a mean difference of 5 months between the two sources and a median of 2 months.

However, we can make a more exact estimation of the difference between the two sources which takes censoring into account if we use a statistic called the 'product limit estimate', or Kaplan Meier, which allows us to estimate average durations (and as we will see, derive survivor functions) for spells of unemployment that includes all spells. The product limit estimate does this by using all the spells

which are still ongoing in each month of the observation window to calculate statistics about the rate at which people are leaving unemployment and thus also, their probability of staying unemployed.

As we can see from Table 3.2, the mean duration for the Register spells is some four months less than that found using the Follow-up Survey (44 compared to 48 months),⁴ although the median duration (i.e. the point at which 50 per cent of the spells are over) is very similar at 31 and 32 months.

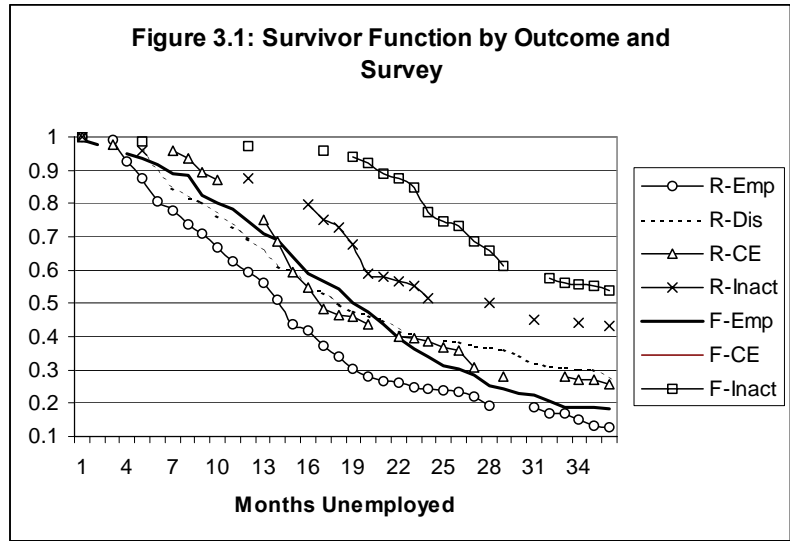
Table 3.2: Product Limit Descriptives of Register and Follow-up Durations (weighted)

	Unweighted N	Mean	Median	Min	Max
Register Data					
– All Cases	1,434	43.9	31	3	380
Follow-up Survey	1,083	48.3	32	1	348
– All Cases					

How close though are the different sources if we examine the different destinations? We can use the same technique to examine different destinations, but here we use it to calculate ‘survivor functions’ which are essentially the proportion still left unemployed at a given duration, and display these using ‘survivor curves’.

The survivor curve shows the proportion having exited unemployment at a given duration and thus the steeper the line, the higher the proportion having exited and the lower the proportion finally left in unemployment. Figure 3.1 shows that across all the destinations, the Register spells tend to be shorter, with the difference being particularly pronounced for spells ending in inactivity, a pattern we suspected may occur. On the other hand, it is difficult to interpret the shorter durations for Register spells rather than Follow-up spells that end in employment. We had imagined that people would seek to remain on the Register even when employed, thus extending the Register spell, but the opposite seems to be the case.

⁴ The average durations of both Register and Follow-up samples are longer than those that would be found if one were to follow all spells that occurred over a long time period. This ‘length-bias’ is due to the fact that a ‘stock’ sample of the unemployed (those unemployed at a particular point in time) will contain more long term unemployed. Here the long term unemployed were over sampled, but even if we reweight for this, a proportion of the short-term could also be expected to become long-term in time.



Overall, the results in this section suggest that the durations that we observe using Register data are very close to those found using the Follow-up Survey, but that the two sources are not identical. Although we do not have a ‘true’ measure of duration, these results suggest that the Register estimate should be seen as a conservative estimate of the actual length of unemployment spells with many people reporting substantially longer spells.

3.3 A Descriptive Analysis of Register Durations

In this section we build on the analysis in the last section by examining durations of unemployment, as found using the Register data for the two regions (in the last section we used Galway alone). However, here we concentrate on exits from the Register to employment. We do this for three main reasons. First, the central aim of this report is to examine the processes which influence exit from the Live Register, but a central concern are the factors that lead to employment. This underlines the fact that the destination to which people leave once they have left the Register is at least as important as the duration before they left. Second, certain exit processes and consequent durations are more complex than others. For example, although exits to the Community Employment scheme will be influenced by a number of factors, the decision to place people on this scheme is made directly by FÁS and so the duration before this occurs is, to a certain extent, defined by that agency. Third and lastly, as we will be using descriptive techniques to examine the impact of different factors on exit, doing this for all exit destinations would be impractical. In the next chapter we will be using comparative risk multi-variate duration models to look at the process in more detail. As we saw in the last section, a large proportion of those who ‘disappeared’ from the Register also went to employment, thus here we define an exit from the Register as being either a move to employment or leaving the Register without

detailing the destination to the DSFA, which as we saw below is likely to actually be a move to employment.

It is important to underline that the Register data used in this section for the Galway and Waterford regions were produced on a directly comparable basis, being drawn in the same manner from the administrative systems of the DSFA. As in the last section however, the move to duration data makes the subject of this chapter rather more complex than that of the last. In the last chapter we talked of two broad groups called the long- and short-term unemployed. Though we discuss these groups as if they are wholly separate populations, in reality they are of course just simplifications of a more complicated situation in which individuals with certain characteristics leave unemployment earlier leaving those with more disadvantageous characteristics in unemployment for longer. Over time the proportions of those with different characteristics comes to reflect these processes and we end up with the descriptive picture laid out in the previous chapter.

We can recover some of this process by using the samples of unemployed taken from the Galway and Waterford Live Registers and plotting the proportions of those with different characteristics against their length of time on the Register. This will give us an, admittedly crude, but useful picture of the characteristics that influence the chance of leaving unemployment, in a manner which more closely replicates the reality of the situation.

In order to carry this out we will be employing the survivor curves just used, i.e. curves that show the proportions of those from particular populations ‘surviving’ on the Register as the period increases. Once again we use the commencement date to derive a period for which the person has been Registered and using the data overall, plot the proportions of those still unemployed after N months from different population groups. Rather than do these plots using arbitrary time periods we again use the ‘product-limit’ estimation, or Kaplan-Meier method.

Figure 3.2 shows the product-limit estimate for groups defined by their region of residence, either Galway or Waterford. In interpreting all the figures in this chapter remember that the steeper the line, the more quickly that group are leaving the Live Register and the lower the line gets on the graph, the fewer people are left on the Register. The fact that the line for the Galway region in Figure 3.2 is, for the vast majority of the figure, below that of the Waterford region, shows that customers in the Galway region tend to leave the Register earlier. The lower point at which the Galway region line crosses the right axis compared to the Waterford line also shows that, after 36 months at least, that more customers will have left unemployment.

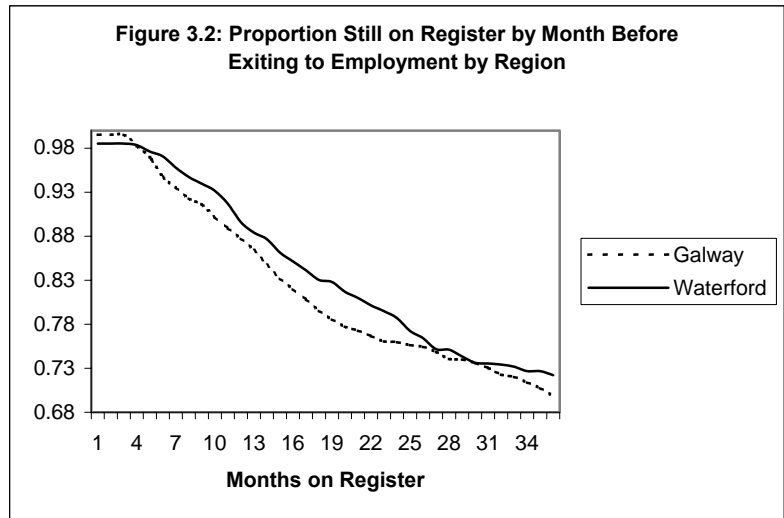
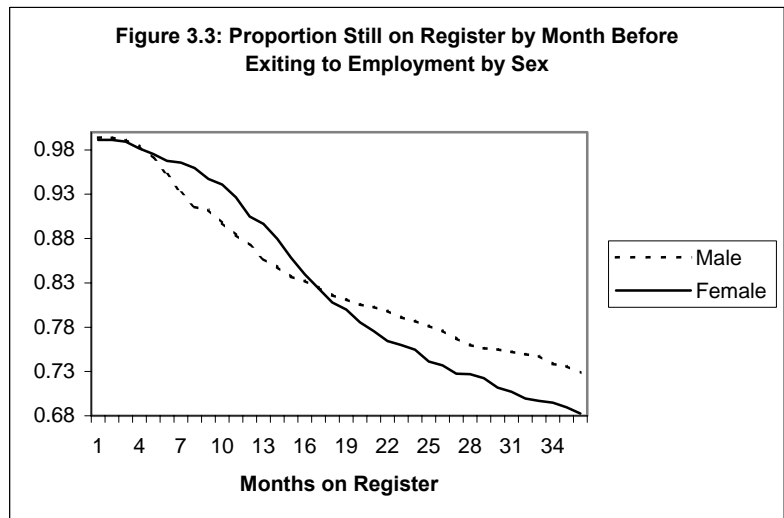


Figure 3.3 shows the curves for men and women and shows that, although men and women leave at an equal rate for the first 6 months, between 6 and 18 months male customers leave at a greater rate. However, at this point the lines then cross again and the female rate of exit speeds up considerably such that the proportion of women who will have exited by three years is 5 per cent higher than among men.



In Figure 3.4 we move to a survivor curve showing the relationship between highest level of education and duration on the Live Register. We would expect that those with higher levels of qualifications would be more likely to be offered jobs and standard economic theory would suggest that the educated would be more productive and thus more likely to leave unemployment – but do we see this relationship here?

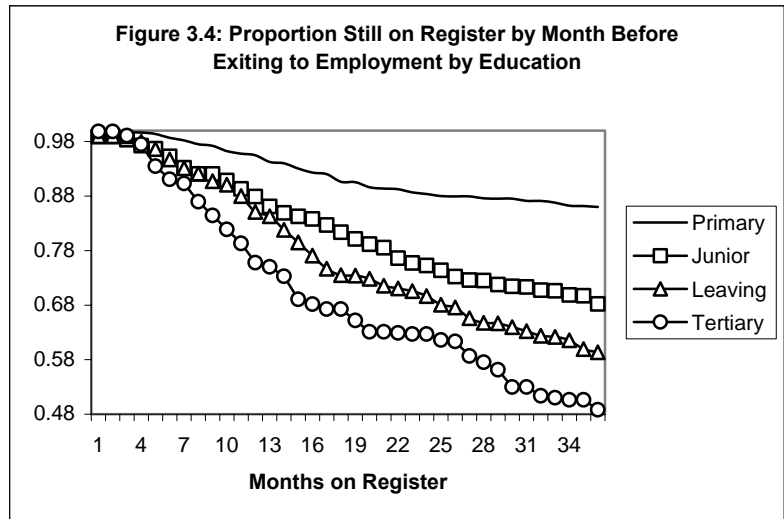
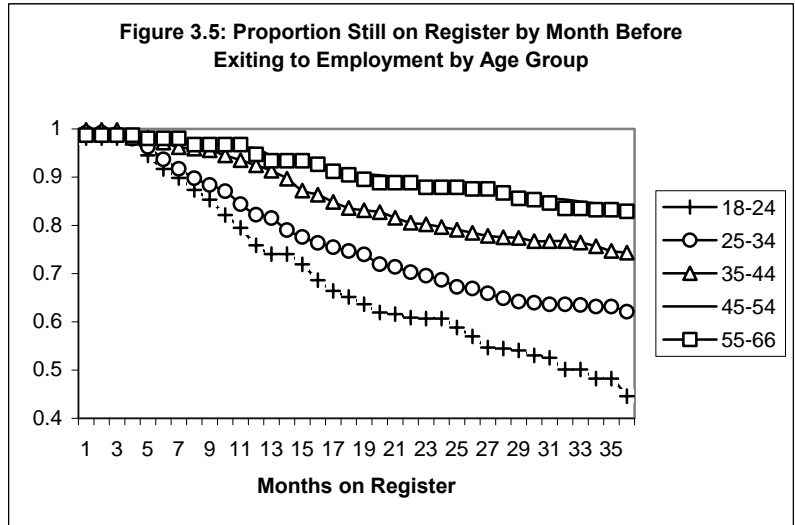
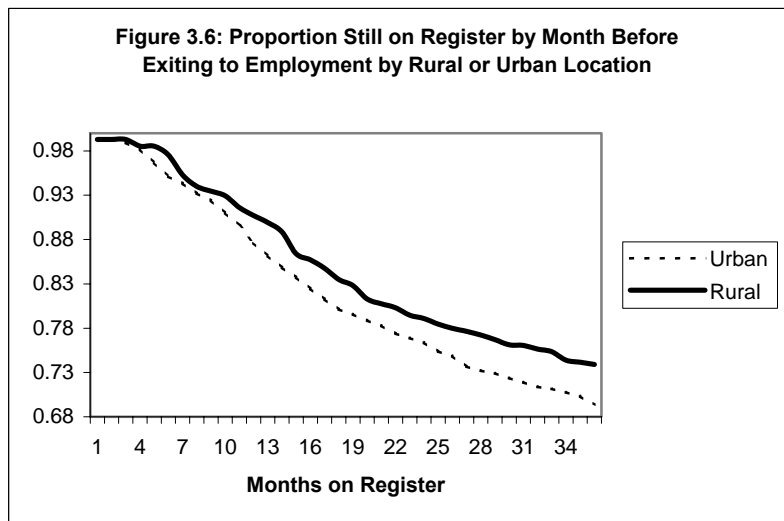


Figure 3.4 shows that we do indeed see the expected pattern with those with Primary or no formal qualifications having the shallowest line which ends at three years duration with around 86 per cent of people still unemployed. As we then look at each additional qualification the track of the survivor curve becomes increasingly steep and the terminal proportion lower. Whereas around 68 per cent of those with a Junior Certificate will remain unemployed after 3 years, 59 per cent of those with a Leaving Certificate will still be unemployed and only 49 per cent of those with a third level qualification.

In Figure 3.5 we move on to an analysis of the relationship between age and duration on the register. In the last chapter we saw that older respondents were far more likely to be long-term unemployed, thus does this vulnerability emerge here also? Figure 3.5 shows that there is a strong age related pattern with younger groups leaving far earlier than older groups, the only exception being those aged over 45 years who are almost indistinguishable from those aged 55 years or more. The line for the group aged between 18 and 24 years drops quickest with around 15 per cent of respondents having left the register at 1 year and around 45 per cent remaining by 36 months. For those aged between 25 and 34 years the rate of exit is significantly lower with almost two-thirds remaining on the register after 3 years. For those aged over 34 years the rate of exit is slower again with only 7 per cent having left by 1 year and almost three-quarters remaining on the Register at 3 years. For the two oldest age groups, only 5 per cent will leave before 1 year and 83 per cent will remain unemployed after 3 years.



Lastly, in Figure 3.6 we move on to the analysis of whether urban/rural location makes a difference in duration. *A priori*, we would expect that being in a rural location would present a lower number of job opportunities and present transport difficulties, and this does seem to be so with those in rural locations exiting the Register at lower rates.



At 12 months 3 per cent more urban customers will have left the Register and this margin increases over time so that at 3 years whereas 69 per cent of urban customers remain unemployed this is true of 74 per cent of rural customers. Tests show, however, that 95 per cent confidence intervals around these estimates overlap showing that the difference is not significant statistically.

3.4 Conclusions

In the last chapter we compared and contrasted the two samples of unemployed people drawn from the Live Register in Galway and Waterford. In this chapter we have extended this analysis by examining the duration of spells on the Register. The duration of a spell is a crucial dimension to the experience of unemployment. Although unemployment will be rarely welcomed, short spells will have little impact on the individual and their family and may even give the person time to find a more suitable job which will be more stable and perhaps more rewarding. On the other hand, a long spell of unemployment will often have severe financial consequences as well as impacting on the psychological and social life of both the individual and family.

We were fortunate that the data available to us included measures of duration from both the Live Register and the Follow-up Survey carried out in Galway in the latter part of 2002. This gave us the opportunity to compare the duration of unemployment spells at the individual level as seen in these two different sources and draw some conclusions about the extent to which the Register is an adequate measure of 'true' unemployment duration. Another important dimension of unemployment alongside duration is the destination which the person left unemployment for (and whether they left at all). Using the two different sources we were able to compare the persons reported destination with that found in the Register. A cross-tabulation of the destinations found in the two sources showed a quite high level of agreement with roughly 50 per cent of cases being in direct agreement and a further 28 per cent being easily explainable. This left a residual of around 22 per cent which may be due to recall or reporting error. Similarly, an examination of the difference in the durations between the two sources showed a high level of agreement with a Kaplan Meier estimate showing that the mean difference between the two sources was just 4 months and the median difference, just 1 month. These small differences give us added confidence in the data being reported in the Live Register, but we should still be aware that the Register estimate is probably a conservative estimate of the true length of unemployment.

The chapter then moved on to a descriptive analysis of the factors that influence the duration of Register spells of unemployment before exit to employment. This caveat is important since there are a range of possible destination states that we could have examined, but chose instead to examine only those that ended in employment. Literature on unemployment in Ireland (Layte and O'Connell, 2001) has shown that a number of variables are important for unemployment duration such as sex, age, education and location. Here we sought to examine these using descriptive techniques in the form of the Kaplan Meier estimate using survivor curves. These show the speed and relative success of different groups in leaving unemployment by plotting the proportion still unemployed at different lengths of unemployment. The steeper and

lower the line, the more quickly the group are leaving unemployment.

The analyses show, as we had already suggested, that higher levels of education, young and living in the Galway region (as opposed to being in the Waterford region) are associated with shorter stays on the Register. Sex also had an influence, but the effect was complex. Men are more likely to leave Register initially but after 18 months their probability of doing so is less than that of women. We found some, albeit small differences between the patterns of exit for respondents in urban and rural areas, but these were not significant.

4. MODELLING REGISTER DURATIONS IN GALWAY: EXPLOITING THE FOLLOW-UP SURVEY

4.1 Introduction

This report has two key aims. The first is to understand the processes that lead to exit from unemployment and in particular, exit from the Live Register. The second aim is to use this understanding of the processes leading to exit from the Register to develop a ‘profile’ of the unemployed, as discussed in the first chapter of this report, that can be used by the DSFA to improve the service that they provide to customers and increase the efficiency and effectiveness of the welfare services and training provided by the public sector at large. In this chapter we tackle the first aim, that of understanding the processes that determine whether and when a person exits the Live Register and the destination to which they leave. As in the last chapter we concentrate on using the Register data since this is our prime interest, but in doing so we make use of data at the individual level that was gathered in the Follow-up Survey. By using this data we gain access to a range of variables that were not available in the original survey carried out by the DSFA in Galway and Waterford in 2000, or in the administrative information which is contained in the Live Register. This is a very important issue since it will have implications for the extent to which new information will need to be collected if a profiling system is to be implemented. For example, if we find that many of the variables that are only contained in the original and Follow-up Surveys are of vital importance in predicting unemployment outcomes, the obvious conclusion is that these variables should be added to the administrative data base if a profiling system is to become a reality.

In the last two chapters we have been able to combine the Live Register samples from Galway and Waterford regions and do a number of useful analyses that show the effect of certain characteristics on people’s prospects for leaving unemployment and thus the Register. Though undoubtedly useful, both these chapters

have used simple analyses using one or perhaps two variables in each instance to give a particular picture of patterns. But life and the processes linked to presence on the Live Register are rarely so simple and it may be that we get a distorted view of the effect of particular variables by looking at each in isolation. For example, we saw in Chapter 2 that the long-term unemployed are more likely to be older, but is this the effect of age, or could it be that older workers are more likely to have lower levels of education and it is this that makes them more likely to be long-term unemployed? It is impossible to come up with a definitive answer to this question until we control for other variables that may ‘confound’ the relationship between the risk of long-term unemployment and the variable of interest.

Accordingly, in this chapter we take a multi-variate approach to the analysis of the Live Register data using statistical models to look at the effect of particular variables net of others in the model. Though a little more complicated, these types of analyses give us far more analytical power. Unlike in the last two chapters however, here we only use the Galway sample. Although it would undoubtedly aid the estimation of the process if we had used the data from the Waterford region, we forgo this aid for two reasons. First, we only have a limited set of variables for the Waterford region that have been derived from the Register data and the first wave of the survey data. The Follow-up Survey was only carried out in Galway and so we can only test the full models on respondents in this region. Second, we will also be seeking to test the explanatory power of the models derived using the Galway data on the Waterford data in Chapter 6. If the Waterford data were used to create the estimates of the effect of different variables, these data could not then be used to test the explanatory power of the model in another region which had not been involved directly in development. In the second part of this chapter we examine recent work on the determinants of unemployment and its implications for the variables that should be used in the current analyses before turning to the data available to us.

In Section 4.3 we explain our modelling strategy and define the models that will be used. In Section 4.4 we discuss problems of length-bias and its implications for our analyses. In Sections 4.5 and 4.6 we turn to the modelling itself and estimate models of exit from the Live Register to various destinations. In Section 4.7 we try to draw some conclusions from the chapter that can be taken forward to the identification of a profile of the unemployed in the next chapter. Throughout this chapter we avoid technical detail and use graphical techniques to describe results. This does mean, however, that the more specialist reader will probably find the level of detail unsatisfactory, thus model estimates and diagnostics can be found in Appendix 4 at the end of this chapter.

4.2 Explaining Unemployment Durations and Destinations

Unemployment has been a subject of economic and social inquiry for most of the twentieth century, but the quantity of literature increased hugely during the 1980s when economic restructuring in most western industrial nations led to unprecedented increases in unemployment and particularly long-term unemployment. The reference to economic restructuring above suggests one particular determinant of being unemployed and the duration of unemployment, possibly the main determinant in times of recession, that of demand in the labour market. In times of recession one not only tends to see an increase in inflows into unemployment but also large falls in exit from unemployment leading to increasing numbers in unemployment (White, 1983). Yet, although Ireland experienced some of the highest rates of unemployment in Europe during the 1980s and first half of the 1990s, by 1996 the economy was expanding quickly and unemployment dropped to a historic low of around 4 per cent by 2000 when the sample of the unemployed being used in this report were collected. Although some of the people in this sample had been unemployed for very long periods, some from before the 1990s, most had become unemployed during the period of growth and so the level of demand was not so much of an issue. Given this, we can look to the interaction of personal characteristics with the labour market for an explanation of why certain people exit unemployment quicker than others.

In economics the standard model of unemployment holds that the duration and outcome of unemployment is a function of a 'matching' process whereby employers try to gain employees with the highest productivity. The unemployed on the other hand seek the most appropriate job where the definition of 'most appropriate' can include the highest level of pay, the right hours of work and right contract type to name just a few dimensions. This brief and rather simple definition underlines the fact that the job search process (see Mortensen, 1977 for greater detail) is two sided with employees as well as employers making decisions about whether a job is appropriate for them. Nonetheless, it is still true that we would expect that those people who are more attractive to employers, perhaps because they have higher levels of skill through education and job experience, would leave unemployment more quickly. As we saw in the last chapter, those with higher levels of education are far more likely to leave unemployment than those with lower levels of education and this process will be replicated for those with particular skills. These 'attractive' characteristics can also include factors such as having a driving licence or having positive mental characteristics such as being willing or a flexible worker. Education and skill has been found to have a large impact on unemployment durations in most national studies (Narendranathan and Nickell, 1985; Narendranathan and Stewart, 1995; Nickell, 1979; Pedersen and Westergård-Nielsen, 1993) and although there has not been a large amount of research on unemployment durations in Ireland, that

which has been done has shown that education is very important (Layte and O'Connell, 2001; Layte and Callan 2001).

Of course, the corollary of this is that certain characteristics are seen as less attractive by employers and these can be such factors as age, having been placed on certain types of government training schemes and having experienced long-term unemployment. Though 'ageism' has become less socially acceptable in recent times, it is still true that older workers and particularly those aged over 45 years are regarded as less malleable and productive. Employers can also regard those approaching retirement as not worth employing since they will leave the organisation on retirement. Age has certainly been shown to impact on unemployment duration (Layte and O'Connell, 2001) in Ireland, though this may also be due to employee decision making as well as employer choice. For example, older people would tend to have been more senior in their previous position and so, even controlling for education, they would be searching for a job with a higher wage (their so called 'reservation wage' would be higher). Older people are also more likely to have more family responsibilities which require a higher income (and moreover which are factored into social welfare payments making their out of work income and 'replacement rate' higher, again increasing the reservation wage) and will probably be looking for a more stable job than younger unemployed people.

An individual's health has been shown to be an important determinant of leaving unemployment. Though many forms of chronic illness are perfectly compatible with full-time work, Irish research (Layte and O'Connell, 2001) found that chronic ill health still had a very strong negative impact on the rate of exit from unemployment controlling for a large number of other factors. This may be because employers are unwilling to employ individuals that they feel will be absent more often because of their illness, but could also be due to the fact that these people themselves stopped searching for work and perhaps moved onto disability benefits which do not require individuals to search for work. The data used in Layte and O'Connell (2001) was survey data and as we saw in the last chapter, this does not redefine individuals as inactive if they are no longer looking for work or have changed benefit type.

Although government training schemes are intended to increase the employability of those taking part, some research has shown that certain types of programmes do not improve the employment prospects of their participants (O'Connell and McGinnity, 1997; Layte and O'Connell, 2001). If we divide Irish active labour market schemes into three broad categories: general training, direct employment and specific skills training, research shows that the first two categories do not significantly improve the employment chances of the person. Irish research has also shown that a history of unemployment has a negative impact on the speed of exit from unemployment, net of the impact of the current spell (although as current unemployment length increases this also decreases the probability of leaving). That is, even though the person may only

have been unemployed for a short period, previous unemployment will be evaluated negatively by employers.

As we have indicated, job search is a two-sided process and certain factors also influence the decisions of individuals to take jobs. Age has a negative influence on the probability of leaving unemployment because older unemployed people will have a higher reservation wage, but we have also seen, this can also be influenced by whether the person has family responsibilities such as a partner and children. Because of the cost of childcare, those with children often find that the available jobs do not pay enough to cover childcare costs and also deliver an acceptable wage. Given the prevailing division of domestic labour in Irish households, this pressure is often felt more by women than men and research shows clearly that women with children are far less likely to leave unemployment whereas men with children are *more* likely to leave.

The incentive for an individual to take a particular job may also be influenced by such factors as the cost and practicality of reaching the place of work. Given this, factors such as the person's location, whether they have a car or other personal transport or whether they live close to public transport would all have an influence on their decision to take a particular job. These variables have not been used in Irish research to date, but research in the UK (Payne *et al.*, 1996) does show that these factors have an impact on outcomes for different individuals once we control for other relevant factors.

4.3 The Modelling Strategy

The central aim of this research is to understand the factors which influence the length of time that an unemployed person will remain on the Live Register. However, as explained both in this chapter and the last, the destination to which this person leaves the Register (and whether they leave at all) is equally as important. It is these two dimensions that we seek to model in this chapter. In doing this, however, we need to use techniques that will allow us to look at the impact of several different factors (or 'variables') at the same time and derive the 'net' effect of each controlling for the other factors in the model – that is, we need to use 'multivariate' techniques. There are a number of different techniques that could be used, the simplest of which would simply estimate the length of time that a person stays on the Live Register conditional on a set of variables (simple linear regression). As seen in the last chapter though, we need to find some way of dealing with the fact that some spells on the Register will not have finished by the time the data were collected from the administrative system, i.e. they are 'censored' by the data collection process. We could just use the collection date as the finish date, but this would give the impression that these spells had finished and this would influence the estimate that we could make of the effect of the variables. Similarly, we could also just delete any unfinished spells, but this has implications for the analysis. The number of censored spells in the Galway data is large (around half of all cases) and so

deleting them would limit the analysis, but it would also bias the results since the factors which influence longer spells (of which a large proportion would be censored) could not be estimated.

Given these problems we need to turn to a class of multi-variate models known as 'hazard rate' or 'duration models' which explicitly model time as well as change from one status to another. These models have a long history and originated in engineering where researchers were attempting to estimate when and if a component would break, but were quickly adopted in medical research (how long will the patient live?) and the social sciences (how long will the person remain unemployed?). They measure the 'propensity' of an individual to change from one status to another in each time period (say a month) by dividing the number of transitions in each month by the number of people who are at risk. This simple calculation produces what is known as a 'transition rate'. Hence, this means that we can take account of those cases which are 'censored' by simply removing them from the group who are at risk, but importantly, only in and after the month at which they were censored. This means that all these cases can be kept in the analysis until they are censored, just as other cases who actually make a transition are kept in the analysis until this occurs (i.e. in and after the month it occurs). Using a statistical model we can then link the transition rate to each factor or variable (using maximum likelihood estimation) and in this way get a quantitative estimate of the effect which each has on the 'propensity' to leave the Register in each month, net of the effect of the other variables in the model.

As suggested, the destination to which people move when they leave the Register is as important as the duration before they do so and from the last chapter we have already seen that there are multiple 'exit' routes from the Live Register. As well as the obvious move to employment, there are also moves into retirement, onto a training course or into Community Employment. People may also move into 'inactivity' because of illness or disablement and thus leave the labour force or they may decide that they will become full-time carers. An adequate model of the process of exit should take all of these exit routes into account, but importantly, should do so simultaneously. For example, if we look at the propensity for an individual to become employed, this risk is not independent of that for joining a CE scheme and so in the transition rate for becoming employed has to be calculated conditional on the risk of also joining a CE course, becoming inactive etc, in the same month. To do this we have to adopt what are called 'comparative risk' models, which as the name suggests calculate the comparative risk of leaving one status for one of several alternative destinations.

4.4 The Problem of Length-Bias

The sample of people used in this report represent an important research resource, but in one respect the manner of their selection presents us with problems. As discussed in Chapter 2, the Galway sample of 1,434 people were drawn at a single point in time from the Live Register of the Galway Region. This sample thus represented a ‘sample’ of those people on the Register at that point in time. Unfortunately doing this introduces ‘length-bias’ which occurs when a cross-sectional sample of people are drawn from ‘flow’ data. Although this may seem a rather abstract statistical problem ‘length-biasing’ may actually interfere with our ability to gain accurate predictions of the effect of different characteristics on leaving the Register. This is due to the sample containing more people who are long-term unemployed than would be found if one followed all people who entered the Register over a sustained period of time. A good analogy is a study of the patients who visit a hospital: if we were to go into the hospital on one day and look at which conditions the patients had we would see more of those conditions that took longer to cure because these would have a higher chance of being in the hospital when we visited. Yet these cases may represent a smaller proportion of the actual caseload than another condition which was more numerous, but which was dealt with quickly.

Luckily an answer to this problem can be found in the type of model that we use to estimate the ‘propensity’ to leave unemployment. Standard duration models need rather complex adjustments to take account of length-bias, but if we adopt a model called the ‘discrete-time’ hazard rate model this takes care of this problem (see Jenkins, 1995).

4.5 The Variables

The last section outlined a number of variables that should be included in the modelling process. In the Galway data available (the original survey, the Follow-up Survey and the Register data) we have access to a range of variables on the same individuals and so we are in a good position to measure many of the processes just outlined. However, as with all modelling exercises we have to work within the constraints of the data available to us. Table 4.1 below lists the variables available to us, which survey they are taken from and any issues about how they are measured.

The variables representing age, sex, marital status and number of children in Table 4.1 are fairly self-explanatory, though it should be noted that age is grouped to make interpretation easier. As suggested older age groups should be less likely to leave unemployment to employment, but they may be more likely to leave to retirement, inactivity or Community Employment. The sex of the person is extremely important, not only as a predictor in its own right (as we saw in the last chapter), but also in changing the effect of other variables. The effect of marriage for instance can be different for men and women with men more likely to leave unemployment and

women less likely to leave. Given this in the modelling to come we use separate models for men and women which allow the effects of all the variables to vary by sex.

The respondent's highest educational attainment takes one of four levels from primary to tertiary and this is accompanied by a variable which also measures whether the person has any difficulties reading, writing or with figures. These measures are quite standard and quantify very important aspects of productivity that employers are seeking. A variable representing whether the person has been placed on a Social Employment Scheme, Community Employment Scheme or FÁS Jobs Initiative is also included. As suggested this may have both positive and negative effects on outcomes since it could imply greater skills on the part of the respondent (if it were regarded as training), but may also be regarded as a signal of long-term unemployment and low productivity by employers.

Two variables are included which measure whether the respondent has transport in the form of a car or whether they live on, or near a bus route, and these would be expected to be positive contributors to leaving the Register to employment. Similarly, a variable representing whether the person has a licence is included and this should be an asset to finding employment.

Table 4.1: Variables Used in Models

Variable	Survey	Explanation of Variable
Age	All	Age in month grouped into categories: <25, 25-34, 35-44, 45-54, 55+
Sex	All	Sex of Respondent
Marital Status	All	Single, married, widowed, separated or divorced
Number of Children	Register	Grouped into 0, 1 to 2, 3+
Educational Level	Original	Highest education grouped into Primary, Junior Cert., Leaving Cert., tertiary
Location	Original	Urban/rural category based on location size
Literacy	Original	Has the respondent difficulty with reading, writing or figures?
Employment Training	Original	Has the respondent participated in SES, CE or FÁS Jobs Initiative?
Transport	Original	Does the respondent own a car?
Public Transport	Original	Does the respondent live on a bus route?
Driving Licence	Original	Has the respondent a full driving licence?
Motivation	Original	Has the respondent ever thought about moving in order to take up a job?
Health Status	Follow-up	Respondent's self rating of their health from 'very good' to 'very bad'
Ever Worked	Follow-up	Has the respondent ever held a job?
Experience of Unemployment	Follow-up	Months spent unemployed in the last 5 years
Experience of Full-Time Caring	Follow-up	Months spend as a full-time carer in the last 5 years

The 'motivation' of the person to leave the Register, or more accurately, to get employment, is a complex concept and is not easily measured. This variable is often referred to as important in the literature, even though often it is not measured. Here we use a variable from the original survey, which asks whether the person has ever considered moving in order to take up a job.

Having an extensive employment history is likely to be a good predictor of one's employment chances and in the opposite fashion having a variable to represent lack of employment history should be a good predictor of failure to get a job. As such we used a variable

from the Follow-up Survey which measures whether the person has ever had a job.

We measure the health of the person using a question from the Follow-up Survey which asks the respondent to rate their own health on a scale from 'very good' to 'very bad' via 'good', 'fair' and 'bad'. It is clear that this cannot summarise the health status of an individual, but it has been repeatedly shown to be a very good indicator of outcomes both for employment and life expectancy. We expect that worse health will delay exit to employment but may well increase the rate of exits to inactivity.

Finally, two variables are used to measure the person's employment history in terms of time spent in unemployment and time spent as a full time carer. Both are measured as the proportion of the last five years that has been spent in each role and each should have a negative effect on leaving to employment, but perhaps a positive impact on exits to inactivity and Community Employment.

As shown by Table 4.1, some of the variables, notably those for history of unemployment and caring, whether having worked and health were only gathered in the Follow-up Survey which unfortunately suffered from some non-response. Non-response is the situation when people who have taken part in a previous survey either refuse to take part in a follow-up survey, or cannot be traced. Of the original respondents 1,083 also took part in the later survey which is a very respectable response rate of 76 per cent, but the loss of 351 individuals means that we cannot estimate a model for the full sample using all the variables in Table 4.1. This situation is made worse by non-response on particular questions which further decreases the available sample to 906 individuals. Because of this we estimate the models in two steps with the first containing only the Register and Original sample variables and all 1,434 cases and the second containing all the variables but only 906 individuals. Although the loss of 528 cases and the addition of four more variables might not have a serious impact on the models, in this case, unfortunately, the non-responding individuals tended to be younger, better educated, more advantaged and thus more often short-term unemployed. We tackle this differential non-response in two ways. First, we create weights which when used return the sample to the distribution of characteristics found among the 1,434 cases. Second, we test the impact of this change by estimating the models both ways: both with and without follow-up variables. As well as estimating models with and without follow-up variables we also estimate individual models for either sex and then a combined model including both men and women.

Finally, in estimating the models of exit from the Register we need to take into account the fact that many of the respondents in the sample would have been activated through the 'Employment Action Plan' (EAP) during their period on the Register and this may well have affected both their duration on the Register and their final destination. The EAP was adopted by the Irish Government in

response to the European Employment Guidelines which requested all EU states to formulate preventative strategies to combat long-term unemployment based on early and systematic intervention to re-integrate unemployed people back into the labour market. This was primarily to be achieved through active labour market policies, that is by providing them with the necessary skills to improve their employability. In Ireland, the EAP scheme was first instituted on September 1st 1998 at which point all young people aged under 25 years who had reached six months on the Register were referred by the (then) Department of Social, Community and Family Affairs to FÁS for interview. From the 1st March 1999, all persons under 25 years who reached 18 months on the Register were referred, as were those aged 25-35 years approaching 12 months on the Live Register from May 1st onward. In February 2000 the process was extended to the remaining group aged 35-54 years as they became unemployed for 12 months or more. Those included in the EAP were first sent a letter inviting them for interview at FÁS after which they were allocated an intervention by FÁS or were designated ‘not-progression ready’ and were returned to the DSFA. Although we do not have room to fully detail the impact of the EAP here, it is clear that the scheme had a substantial impact on the numbers on the Live Register who had crossed these thresholds, although the true nature of this effect and its extent are still very much debated. Nonetheless, the scheme is likely to have impacted on many of the respondents in this study and as such needs to be taken into account.

In studying the process of leaving the Register, it would be ideal if all respondents experienced the same conditions and aids so that we could analyse the impact of their own characteristics net of any other factors. Unfortunately, this is not true here as some respondents were not included in the EAP process as either their unemployment spell was not sufficiently long (i.e. they had left the Register before becoming eligible), or they had already passed the threshold periods for inclusion. On the other hand, some were fully integrated into the process, were sent the letter of invitation and attended a meeting with FÁS before being allocated some form of intervention. In the analyses to come we try to control for the impact of being included in the EAP process by using two variables to represent whether the person was sent the letter of invitation to be interviewed by FÁS and whether they had then been interviewed. This strategy is not fully satisfactory since we do not include information on whether the person was given an intervention or what type (this was not available), but it should still allow us to control for the major impact of the EAP process.

4.6 Model Results

In this section we describe the results of the models estimated. We try to do this in a non-technical fashion by describing the effects rather than giving tables of coefficients, but the reader can find the full models with coefficients and diagnostics in the Appendix to this chapter. As explained, we estimate six models in all: a male, female

and combined model for the sample with and without follow-up data. Each model has results for three possible destinations: moves to employment, to Community Employment and to ‘other’ destinations which includes retirement, full-time caring, illness/disability and training. The tables in this chapter show the effect of the variable as being either positive (increasing the risk of leaving the Register) or negative (decreasing the risk of leaving the Register) and only those effects which are statistically significant at a probability of 95 per cent are shown.

MODELS WITHOUT FOLLOW-UP

Looking first at the model for the whole sample (men and women) without follow-up variables in Table 4.2, we can see that the EAP process had a significant positive effect on transitions to all three destinations (i.e. it made them more likely to happen). For moves to employment, being called for interview (rather than just attending an interview) increases the probability that the person will move to employment that month by 2.3 (i.e. a person called for interview is 2.3 times more likely to become employed that month). Attending an interview further increased the probability by 1.7 in each month that the person would leave for employment (as opposed to remaining on the Register). For movements to CE the effect was even greater with respondents 4.5 times more likely to move to a CE course after interview and 5.5 times more likely after visiting FÁS. For other types of moves, only being called for interview was significant, but the effect was very large.

Although the effect for age on becoming employed was negative as expected (i.e. older people were less likely to move), this was statistically significant only for the 45-54 year age group. Interestingly, the oldest age group were more likely to move to ‘other’ destinations which of course includes retirement. Although there were no significant effects for marital status, having three or more children did lead to a quite large reduction in the probability that the person would move to employment. Also as expected, all of the lower education categories slowed down exits to employment relative to having third level qualifications, although only the lowest level (Primary or less) was significant, as was having literacy and numeracy problems (with the effect literacy and numeracy being larger).⁵

⁵ In all of these multivariate analyses the reference category is the category against which we measure an effect. For example, in Column 1 of Table 4.2, the Employment equation, the positive effects of the ‘aged 45-54’ years term means that those in the 45-54 year age group are more likely to move to employment than those in the 17-24 year age group which is the reference category for age groups.

Table 4.2: Results of Model Predicting Exit from the Live Register to Different Destinations (Without Follow-up Variables – Men and Women)

Variable	Employment	C.E	Other
Interviewed Under EAP	+	+	+
Activated Under EAP	+	+	
Respondent is Male	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Respondent is Female			
Aged 17-24 years	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Aged 25-34 years			
Aged 35-44 years			
Aged 45-54 years	-		
Aged 55-64 years			+
Single	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Married			
Divorced/Separated/Widowed		-	
No Children	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
1 or 2 Children			
3+ Children	-		
Tertiary Education	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Primary Education Only	-		-
Junior Certificate			
Leaving Certificate			
Urban Location	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Rural Location			
Has Literacy Problems	-		
Has attended CE, SES or FÁS Jobs Initiative		+	
Has Car	+		
Has Driving Licence			
Has Access to Public Transport			
Has Thought of Moving for a Job			

Although having attended an SES, CE or Jobs Initiative course did not impact significantly on exits to employment, it was a very large positive influence on moving onto a CE course whereas having a car was more likely to lead to employment.

Table 4.3 shows the effects in the model for men alone. Here we see rather similar effects to the last model, although fewer were significant statistically because of the lower number of cases. However, as before age was a negative influence on leaving to employment as was having a lower level of education and a higher number of children. On the other hand, having a driving licence was a positive characteristic which increased the likelihood of moving to employment. Unlike in the model for both men and women, here older age groups were far more likely to leave the Register for a CE course and being in a rural location and having previously been on a CE course also increased the probability of this outcome.

Overall the model for men supports many of the hypotheses discussed earlier about the importance of age and education/skills as influences on one's likelihood of getting employment, but it also shows that older age groups and those in rural areas are far more likely to join the CE scheme.

Table 4.3: Results of Male Model Predicting Exit from the Live Register to Different Destinations (Without Follow-up Variables)

Variable	Employment	C.E	Other
Interviewed Under EAP	+	+	+
Activated Under EAP			
Aged 17-24 years	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Aged 25-34 years		+	
Aged 35-44 years	-	+	
Aged 45-54 years		+	
Aged 55-64 years			+
Single	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Married			+
Divorced/Separated/Widowed			
No Children	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
1 or 2 Children			
3+ Children	-		
Tertiary Education	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Primary Education Only	-		-
Junior Certificate			
Leaving Certificate			
Urban Location	<i>Reference</i>	<i>Reference</i>	<i>Reference</i>
Rural Location		+	
Has Literacy Problems			
Has attended CE, SES or FÁS Jobs Initiative		+	
Has Car	+		
Has Driving Licence		+	
Has Access to Public Transport			
Has Thought of Moving for a Job			

In Table 4.4 we turn to the female models of exit which were not as successful as those for the total sample and for men alone, primarily because the sample available was smaller and thus the effects have to be very large to be significant. We do, however, see similar effects as before for the EAP process, with being invited for interview leading to a large increase in the probability that women will leave the Register for a Community Employment Scheme or to another status such as full-time carer. Education level also seems to have an effect here as it did in previous models with primary education or less having a very significant negative impact on whether one will leave the Register for employment. As shown in the next chapter however, low levels of significance do not necessarily mean that the variables in these models do not contribute to the prediction of the different outcomes.

Table 4.4: Results of Female Model Predicting Exit from the Live Register to Different Destinations (Without Follow-up Variables)

Variable	Employment	C.E +	Other +
Interviewed Under EAP			
Activated Under EAP			
Aged 17-24 years	Reference	Reference	Reference
Aged 25-34 years			
Aged 35-44 years			
Aged 45-54 years			
Aged 55-64 years			
Single	Reference	Reference	Reference
Married			
Divorced/Separated/Widowed			
No Children	Reference	Reference	Reference
1 or 2 Children			
3+ Children			
Tertiary Education	Reference	Reference	Reference
Primary Education Only	-		
Junior Certificate			
Leaving Certificate			
Urban Location	Reference	Reference	Reference
Rural Location			
Has Literacy Problems			
Has attended CE, SES or FÁS Jobs Initiative			
Has Car			
Has Driving Licence			
Has Access to Public Transport			
Has Thought of Moving for a Job			

MODELS WITH FOLLOW-UP VARIABLES

The Follow-up Survey allows us to examine the contribution of some other variables to the prediction of stays on the Register: the health status of the person, whether they have ever worked and the proportion of the last five years that they have spent in unemployment and full-time caring. Unfortunately for us however, the Follow-up Survey suffered from non-response (i.e. people originally interviewed in May/June 2000 either could not be traced, or refused to take part in the Follow-up Survey), reducing still the small number of cases available for analysis. This ‘attrition’ can seriously impact on estimates particularly if the people that do not respond are similar in some fashion leading to a systematic error. If we look at the characteristics of those that did not respond to the second interview they do seem to share similar characteristics, viz, they tend to be younger, be better educated, more skilled, female and generally more likely to leave the Register after a shorter period. This presents us with problems for analysis since to analyse the sample as is could lead to bias in the results. In an attempt to limit the impact of the systematic attrition we designed ‘weights’ for the data using a number of characteristics. This weight returns the distribution of the sample back to that in the Original survey by ‘weighting-up’, or making more important those in the sample with characteristics similar to those who did not take part in the second wave. However, this cannot make up for the fact that less people responded to the survey overall leading to less variation in the sample. For example, of

the 906 people in the Galway Region available for analysis in the Follow-up Survey, only 28, 12 men and 16 women left the Register before 1 year of duration. Although this group can be ‘weighted-up’ in an attempt to take account of attrition, the fact remains that such a small number of people with this characteristic restricts the variation in the file. Nonetheless, in this section we use the weighted data to model duration on the Register.

MODEL RESULTS WITH FOLLOW-UP VARIABLES

Rather than give a full listing of the results of the models as we did in the last section, here we present only those aspects of the existing models that change with the new models compared to those previously estimated and focus in particular on the effect of the Follow-up Survey variables (the full models are displayed in the Appendix to this chapter in Tables A4.4 to A4.6).

Looking first at the model for men we find that the smaller sample means that very few of the effects that we found using the large sample are significant, although the control variables for the impact of the EAP process remain significant, in the same direction and of the same magnitude. We do not, however, see any effects for the age of the person or their educational qualifications which were important in the previous models. On the other hand, we see very strong and significant effects for some of the additional variables in the model. For example, the proportion of the last five years spent in unemployment is very significant and is negatively related to the chance that the person will leave the Register for employment (i.e. more unemployment leads to slower exit). Similarly, having less than good health also decreases the rate at which the person will leave the Register.

For male moves to CE we see rather more of the effects shown in the larger model including having participated in the past in CE/SES and having a driving licence, but age is not a significant factor in these models. As in the model of exits to employment we see strong effects for the impact of health on moves to CE with worse health slowing down transitions to CE. In terms of moves to other destinations, the effect of age remains, but there are no other significant effects apart from the impact of being called for interview under the EAP process.

For women, we see very little which is significant in the model of moves to employment, although the variable representing the proportion of the last five years spent in caring is significant and very powerful suggesting that this is an important variable. This variable also turns out to be a good predictor of not moving into a CE position, along with the woman’s proportion of time spent unemployed and her health status. Interestingly, we also see effects for the woman’s education and age becoming significant here unlike in the larger model.

Finally, the model for both men and women reinforces the importance of the variables for past unemployment/caring and

health status. Both are very significant and slow exit from the Register to employment, although the model of exit to employment using the smaller sample does lose many of the effects for age and education seen using the large sample.

4.7 Conclusions

Before we can design a profile which can be used to identify those entrants to the Live Register who will stay long-term, we first need to understand the general factors which influence the duration of stays on the Register. In this chapter we have attempted to do this using ‘comparative risk’ hazard rate models which allow us to control for the censoring of the data while establishing the impact of different characteristics on durations. What is ‘comparative’ about these models is that they simultaneously estimate the risk of leaving the Register to a number of different destinations which is important since different destinations are associated with different exit processes. For example, among male clients on the Register, older age groups were found to be less likely to leave the Register to employment, whereas older respondents were far more likely to leave to a Community Employment position. We can explain this patterning using the discussion at the beginning of this chapter which discussed the problems which older unemployed men have in finding appropriate employment, e.g. the higher wages they require, a more specific occupation and employer concerns about productivity. As the period of unemployment increases the men become more likely to be offered a CE position. It was also clear among men that the EAP process was a major factor in leading men onto CE, but only after interview, whereas simply being sent the invitation for interview increased the probability of men leaving for employment.

Among both men and women it was clear that lower educational attainment decreased the probability of leaving the Register to employment, a well documented pattern based on the lower demand for unskilled workers in the Irish labour market. Among men however, we also see that having a larger number of children also slows down exits to employment, possibly due to the impact that having more children has on the incentive to take a job. As explained, unemployment benefits take child and adult dependents into account increasing the income of the person and drawing it closer to the income that they can earn in the labour market. This may present a disincentive to take a job, particularly in the case of low skilled workers whose wage offers may be only slightly higher than their benefits. It was also clear from these models that a means of transport helped the unemployed to leave the Register and in particular, having a car for men. As we will see in the next chapter, these practical considerations are very important for employment chances.

Using the larger set of variables that were available to us using the Follow-up Survey we also found that health status had a major bearing on the speed at which people left the Register and if they would find employment. Among both men and women having less

than fair health leads to a significant increase in the time that it took to leave the Register and a much greater chance of not leaving at all. Similarly, we also found that if a person had experienced long periods of unemployment in the last five years, or been out of the labour market caring for others (although this only applied to women), this also slowed down their exit from the Register considerably.

APPENDIX A4

The models used in this chapter are ‘comparative-risk’ multinomial logit discrete time hazard rate models. Models are estimated using person periods of one month, clustered on the individual to control for the fact that observations are correlated within but not between individuals. The baseline hazard was shown to be weibull and thus a log transformation of the duration at t is used.

Table A4.1: Results of a Multinomial Logit Discrete-Time Hazard Rate Model of Exit from the Register to Three Destinations (Men without Follow-up Variables)

Variable	Employment		C.E		Other	
	β	Sig.	β	Sig.	β	Sig.
Log (Duration)	-0.01	***	0.00	n.s	0.00	**
Invited for EAP Interview	0.91	***	0.68	n.s	1.97	***
Interviewed Under EAP	0.46	n.s	2.86	***	-0.78	n.s
Aged 25-34 years	-0.36	n.s	20.29	***	-0.22	n.s
Aged 35-44 years	-0.72	*	20.47	***	-0.18	n.s
Aged 45-54 years	-0.55	n.s	20.40	***	0.09	n.s
Aged 55+ years	-0.47	n.s	21.22	n.s	2.34	***
Married	0.14	n.s	0.45	n.s	-0.37	n.s
Separated/Div/Widowed	-0.04	n.s	-0.73	n.s	0.74	*
1 or 2 Children	-0.29	n.s	-0.58	n.s	-0.07	n.s
3+ Children	-0.97	*	-0.72	n.s	-0.03	n.s
Primary Education	-0.82	*	0.02	n.s	-1.20	*
Junior Certificate	-0.27	n.s	-0.32	n.s	-0.82	n.s
Leaving Certificate	-0.19	n.s	-0.05	n.s	-0.34	n.s
Rural	0.01	n.s	0.83	**	-0.24	n.s
Literacy Problems	-0.37	n.s	0.35	n.s	-0.04	n.s
Participated in SES or CE	-0.08	n.s	1.19	***	-0.29	n.s
Have Car	0.67	**	-0.51	n.s	0.27	n.s
Have Licence	0.05	n.s	0.73	*	-0.48	n.s
Live on Bus Route	0.17	n.s	0.36	n.s	-0.18	n.s
Would Move for a Job	0.18	n.s	0.28	n.s	-0.02	n.s
Constant	-4.18	***	-29.1	***	-5.73	***
Log-Likelihood	-3,925.0998					
N of Cases	948 Individuals or 65,596 Person Months					
Pseudo R ²	0.11					

Key: n.s: Not Significant *: $P > 0.05$ **: $P > 0.01$ ***: $P > 0.001$

Table A4.2: Results of a Multinomial Logit Discrete-Time Hazard Rate Model of Exit from the Register to Three Destinations (Women without Follow-up Variables)

Variable	Employment		C.E		Other	
	β	Sig.	β	Sig.	β	Sig.
Log (Duration)	0.00	n.s	-0.02	n.s	0.00	n.s
Invited for EAP Interview	0.69	n.s	2.27	**	1.51	**
Interviewed Under EAP	0.80	n.s	1.11	n.s	-0.12	n.s
Aged 25-34 years	0.35	n.s	1.07	n.s	-0.83	n.s
Aged 35-44 years	0.19	n.s	1.17	n.s	-0.87	n.s
Aged 45-54 years	-0.28	n.s	1.28	n.s	-1.19	n.s
Aged 55+ years	0.77	n.s	-0.44	n.s	0.76	n.s
Married	0.35	n.s	-1.15	n.s	-0.26	n.s
Separated/Div/Widowed	0.33	n.s	-1.18	n.s	0.33	n.s
1 or 2 Children	-0.54	n.s	0.02	n.s	0.02	n.s
3+ Children	-0.88	n.s	0.06	n.s	0.67	n.s
Primary Education	-1.10	**	0.17	n.s	-0.71	n.s
Junior Certificate	-0.52	n.s	0.93	n.s	0.40	n.s
Leaving Certificate	-0.12	n.s	0.91	n.s	0.19	n.s
Rural	0.13	n.s	0.39	n.s	-0.68	n.s
Literacy Problems	-0.57	n.s	-0.13	n.s	0.04	n.s
Participated in SES or CE	-0.19	n.s	0.76	n.s	-1.12	n.s
Have Car	-0.13	n.s	-1.61	n.s	0.00	n.s
Have Licence	0.11	n.s	0.48	n.s	0.28	n.s
Live on Bus Route	0.17	n.s	-0.27	n.s	-0.51	n.s
Would Move for a Job	0.22	n.s	-0.23	n.s	-1.19	*
Constant	-4.90	***	-7.66	***	-4.94	***
Log-Likelihood	-2,020.821					
N of Cases	486 Individuals or 23,982 Person Months					
Pseudo R ²	0.0875					

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

Table A4.3: Results of a Multinomial Logit Discrete-Time Hazard Rate Model of Exit from the Register to Three Destinations (Men and Women without Follow-up Variables)

Variable	Employment		C.E		Other	
	β	Sig.	β	Sig.	β	Sig.
Log (Duration)	-0.01	***	0.00	n.s	0.00	**
Invited for EAP Interview	0.84	***	1.52	**	1.79	***
Interviewed Under EAP	0.54	*	1.70	***	-0.60	n.s
Female	-0.16	n.s	0.50	n.s	0.09	n.s
Aged 25-34 years	-0.10	n.s	0.94	n.s	-0.45	n.s
Aged 35-44 years	-0.40	n.s	1.04	n.s	-0.41	n.s
Aged 45-54 years	-0.48	*	1.16	n.s	-0.45	n.s
Aged 55+ years	-0.01	n.s	1.44	n.s	1.70	***
Married	0.22	n.s	-0.25	n.s	-0.27	n.s
Separated/Div/Widowed	0.11	n.s	-1.35	*	0.60	n.s
1 or 2 Children	-0.42	n.s	-0.13	n.s	-0.07	n.s
3+ Children	-0.96	**	-0.11	n.s	0.18	n.s
Primary Education	-0.89	***	0.27	n.s	-0.91	*
Junior Certificate	-0.34	n.s	0.20	n.s	-0.27	n.s
Leaving Certificate	-0.15	n.s	0.35	n.s	-0.08	n.s
Rural	0.10	n.s	0.59	n.s	-0.44	n.s
Literacy Problems	-0.42	*	0.26	n.s	-0.06	n.s
Participated in SES or CE	-0.13	n.s	1.10	***	-0.54	n.s
Have Car	0.36	*	-0.81	n.s	0.15	n.s
Have Licence	0.06	n.s	0.59	n.s	-0.19	n.s
Live on Bus Route	0.20	n.s	0.13	n.s	-0.36	n.s
Would Move for a Job	0.17	n.s	0.15	n.s	-0.39	n.s
Constant	-4.37	***	-9.09	***	-5.39	***
Log-Likelihood			-6180.0149			
N of Cases	1,434 Individuals or 89,578 Person Months					
Pseudo R ²	0.0915					

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

Table A4.4: Results of a Multinomial Logit Discrete-Time Hazard Rate Model of Exit from the Register to Three Destinations (Men with Follow-up Variables)

Variable	Employment		C.E		Other	
	β	Sig.	β	Sig.	β	Sig.
Log (Duration)	-0.01	*	0.00	n.s	0.00	*
Invited for EAP Interview	1.13	**	1.69	*	3.32	***
Interviewed Under EAP	0.43	n.s	2.64	**	-1.13	n.s
Aged 25-34 years	-0.49	n.s	17.48	n.s	-0.36	n.s
Aged 35-44 years	-1.05	n.s	17.36	n.s	-0.19	n.s
Aged 45-54 years	-0.50	n.s	17.75	n.s	0.36	n.s
Aged 55+ years	0.00	n.s	16.83	n.s	3.27	**
Married	-0.29	n.s	0.14	n.s	-0.39	n.s
Separated/Div/Widowed	0.12	n.s	0.65	n.s	0.44	n.s
1 or 2 Children	0.69	n.s	-0.45	n.s	0.02	n.s
3+ Children	-0.24	n.s	-0.95	n.s	0.04	n.s
Primary Education	0.28	n.s	0.88	n.s	-0.08	n.s
Junior Certificate	0.67	n.s	-0.88	n.s	1.01	n.s
Leaving Certificate	0.82	n.s	-0.99	n.s	0.62	n.s
Rural	-0.08	n.s	0.51	n.s	-0.10	n.s
Literacy Problems	-0.32	n.s	-0.24	n.s	-0.15	n.s
Participated in SES or CE	0.60	n.s	1.13	*	-0.15	n.s
Have Car	0.73	n.s	-0.13	n.s	0.44	n.s
Have Licence	-0.24	n.s	1.04	*	-0.81	n.s
Live on Bus Route	0.38	n.s	0.28	n.s	-0.51	n.s
Would Move for a Job	0.27	n.s	-0.68	n.s	-0.18	n.s
Has Worked in Past	-0.05	n.s	17.60	n.s	-0.10	n.s
Prop. Last 5 Yrs Caring	-6.09	n.s	-1.63	n.s	-0.37	n.s
Prop. Last 5 Yrs Unemp.	-1.53	***	-0.57	n.s	-0.48	n.s
Good Health	-0.38	n.s	-1.36	*	-0.23	n.s
Fair Health	-0.88	*	-0.89	n.s	-0.21	n.s
Bad or Very Bad Health	-2.05	***	-2.06	*	0.43	n.s
Constant	-4.43	***	-43.3	n.s	-7.09	***
Log-Likelihood			-1,832.7765			
N of Cases	628 Individuals or 45,251 Person Months					
Pseudo R ²	.1685					

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

**Table A4.5: Results of a Multinomial Logit Discrete-Time Hazard Rate Model of Exit from the Register to Three Destinations
(Women with Follow-up Variables)**

Variable	Employment		C.E		Other	
	β	Sig.	β	Sig.	β	Sig.
Log (Duration)	0.00	n.s	-0.01	n.s	0.01	*
Invited for EAP Interview	0.66	n.s	1.59	n.s	1.50	n.s
Interviewed Under EAP	1.67	**	2.65	**	-0.83	n.s
Aged 25-34 years	1.45	*	0.83	n.s	-1.06	n.s
Aged 35-44 years	0.92	n.s	1.40	n.s	-2.17	**
Aged 45-54 years	-0.75	n.s	3.05	*	-1.94	n.s
Aged 55+ years	1.21	n.s	1.90	n.s	0.31	n.s
Married	-0.43	n.s	0.36	n.s	-0.25	n.s
Separated/Div/Widowed	0.40	n.s	-1.13	n.s	0.33	n.s
1 or 2 Children	-1.62	n.s	0.85	n.s	-0.37	n.s
3+ Children	-1.50	n.s	0.23	n.s	0.68	n.s
Primary Education	-0.40	n.s	3.39	**	-1.60	*
Junior Certificate	-0.12	n.s	3.16	***	-0.72	n.s
Leaving Certificate	0.48	n.s	2.51	**	-0.42	n.s
Rural	0.18	n.s	1.02	n.s	-1.06	n.s
Literacy Problems	-0.53	n.s	-0.37	n.s	-0.01	n.s
Participated in SES or CE	-1.38	n.s	-1.05	n.s	-1.17	n.s
Have Car	0.99	n.s	-1.38	n.s	0.70	n.s
Have Licence	0.13	n.s	-0.41	n.s	-0.39	n.s
Live on Bus Route	0.56	n.s	-0.13	n.s	-0.19	n.s
Would Move for a Job	0.64	n.s	1.22	n.s	-1.11	n.s
Has Worked in Past	0.74	n.s	0.54	n.s	0.30	n.s
Prop. Last 5 Yrs Caring	-2.10	*	-4.41	*	-0.52	n.s
Prop. Last 5 Yrs Unemp.	-1.35	n.s	-3.42	**	-0.39	n.s
Good Health	0.56	n.s	-1.59	n.s	0.70	n.s
Fair Health	-0.16	n.s	-5.05	*	-0.22	n.s
Bad or Very Bad Health	-0.45	n.s	-36.8	***	0.35	n.s
Constant	-6.79	***	-8.25	***	-4.43	*
Log-Likelihood			-964.46325			
N of Cases	278 Individuals or 14,342 Person Months					
Pseudo R ²						

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

Table A4.6: Results of a Multinomial Logit Discrete-Time Hazard Rate Model of Exit from the Register to Three Destinations (Men and Women with Follow-up Variables)

Variable	Employment		C.E		Other	
	β	Sig.	β	Sig.	β	Sig.
Log (Duration)	0.00	n.s	0.00	n.s	0.00	**
Invited for EAP Interview	0.93	**	2.07	**	2.44	***
Interviewed Under EAP	0.70	n.s	1.52	*	-1.06	*
Female	0.30	n.s	1.66	***	0.10	n.s
Aged 25-34 years	0.24	n.s	0.52	n.s	-0.89	n.s
Aged 35-44 years	-0.25	n.s	0.78	n.s	-1.24	*
Aged 45-54 years	-0.49	n.s	1.43	n.s	-0.83	n.s
Aged 55+ years	0.32	n.s	0.28	n.s	1.71	**
Married	-0.13	n.s	0.04	n.s	-0.31	n.s
Separated/Div/Widowed	0.40	n.s	-1.22	n.s	0.48	n.s
1 or 2 Children	-0.37	n.s	-0.07	n.s	-0.01	n.s
3+ Children	-0.81	n.s	-0.07	n.s	0.29	n.s
Primary Education	0.12	n.s	1.78	*	-0.94	n.s
Junior Certificate	0.32	n.s	0.97	n.s	0.00	n.s
Leaving Certificate	0.52	n.s	0.95	n.s	-0.10	n.s
Rural	0.14	n.s	0.51	n.s	-0.49	n.s
Literacy Problems	-0.39	n.s	0.13	n.s	-0.03	n.s
Participated in SES or CE	-0.04	n.s	0.35	n.s	-0.40	n.s
Have Car	0.58	n.s	-0.45	n.s	0.46	n.s
Have Licence	-0.01	n.s	0.32	n.s	-0.55	n.s
Live on Bus Route	0.51	n.s	0.08	n.s	-0.41	n.s
Would Move for a Job	0.32	n.s	0.29	n.s	-0.59	n.s
Has Worked in Past	0.21	n.s	1.60	n.s	0.39	n.s
Prop. Last 5 Yrs Caring	-1.65	***	-2.84	*	-0.05	n.s
Prop. Last 5 Yrs Unemp.	-1.12	**	-1.46	*	-0.29	n.s
Good Health	0.06	n.s	-1.06	*	0.18	n.s
Fair Health	-0.34	n.s	-1.52	**	-0.19	n.s
Bad or Very Bad Health	-1.21	**	-2.26	**	0.32	n.s
Constant	-5.54	***	-10.36	***	-5.61	***
Log-Likelihood			-3,044.381			
N of Cases	906 Individuals or 59,593 Person Months					
Pseudo R ²	.1473					

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

5. EXTRACTING KEY PROFILING VARIABLES FROM THE GALWAY DATA

5.1 Introduction

In the last two chapters we have tackled the first of the two aims of this report: we have developed a better understanding of the factors which determine if, where to and when a person will leave the Live Register. First using descriptive statistics and then more multi-variate methods we have statistically assessed the relationship between factors such as education, age and number of children and the time taken to exit. In this chapter we use these findings to tackle the second aim of this report – that of creating a ‘profile’ of those on the Live Register that can be used to improve the effectiveness of social welfare services and active labour market policies by identifying those people at a high risk of becoming long-term unemployed.

Before going on to discuss the steps taken to develop the profile, it is worth revisiting what we are trying to accomplish in developing a profile and the implications that this has for the analyses in this chapter. For example, although the last chapter produced statistics on exits to Community Employment and inactivity, do we really require these as part of the profiling exercise or should we concentrate solely on moves from the Register in a given period of time? Having examined the aims of profiling in the first section of this chapter we turn in the second to the methodological approach that we take. As in the last chapter this can be rather complex statistically, but we attempt to present it in an accessible manner. In the third section of the chapter we move to an examination of the results of the analyses.

5.2 The Methodological Approach and its Problems

As in other countries (see OECD, 1998), the work in this report hopes to contribute to the development of a profiling system in Ireland that will identify those people who join the Live Register who are likely to become long-term unemployed. This information can then be used to both intervene earlier with that person and tailor the active labour market programmes directed at the individual, and in the process, limit the impact or ‘scarring’ effects which

unemployment has on the individual and the cost of benefits which would be transferred to that person if they were to become long-term unemployed.

Establishing those people at risk of longer-term unemployment is, however, a different task to that undertaken in the last chapter where we modelled the factors influencing overall durations. The factors that predict duration will be similar to those that are effective predictors of being long-term unemployed, but do we also need here to control for the different outcome destinations that people may move to? Certainly different processes will operate for the different outcomes and as already discussed in the last chapter, the Department of Social and Family Affairs already intervene in the exit process by sending customers to FÁS via the EAP process. Durations for those leaving to CE are thus directly under the influence of the Government. This means that for a sizeable proportion of those in our sample, their actual duration on the Register is at best an interaction of the processes discussed in the last chapter and Departmental decisions. However, the question is, does the intervention of government departments in the exit process influence who leaves the Register before one year? If so, we will have problems since the models will have to take the administrative process into account. In fact, if we examine the destinations of those leaving before one year we find that very few people (3 in our Galway sample) exit to CE before 12 months, a pattern true of other destinations such as retirement and full-time caring as well. Given this, a simple dichotomy between long and short term on the Register is an acceptable simplification since the outcome does seem to be determined by processes other than government departments. Thus, instead of modelling the duration that the person would be on the Register and the destination to which they leave, here we will need to model the probability of being long term on the Register, irrespective of the final destination to which people leave.

However, the nature of the sample of the unemployed with which we are working presents us with problems in modelling this outcome.⁶ As described in Chapter 2, the samples of the unemployed drawn from Galway and Waterford both over sampled the long-term unemployed such that 75 per cent of the overall samples were long term on the Register at the time sample selection occurred (that is 1,066 of the 1,434 in the Galway region). Yet a large number of those who were short term at selection would also be expected to become long term (not being long enough on Register at selection). In fact what we see in Galway is that over 75 per cent of those who were short term, subsequently stayed on the Register for

⁶ We should make it clear that these problems in no way stem from errors made in the initial sample selection or data collection. The sample was drawn exactly to over-represent the unemployed so that this group could be studied in more depth, but one of the unintentional consequences of this choice is that there are relatively few short-term unemployed.

12 months or more. This leaves us with only 84 cases where the overall duration on the Register was under 12 months, which is comparatively few cases for analysis. This problem is compounded if we then attempt analyses by sex since the sample of the short-term unemployed will be roughly halved (in fact there are only 33 women among the 84, or 5.6 per cent short term unemployed in Galway). This is a difficult problem and an important issue to solve since the success of the profiling exercise depends to a large extent on the precision of the estimates that can be made from the data. If the estimates are unreliable then the profile could fail to identify those who will enter long-term unemployment, thus failing to solve the current problem and/or falsely identify those who would in fact not become long-term unemployed as heading for this outcome and in doing so create the possibility of 'dead weight' expenditure.

This lack of short-term unemployed people was not as serious a problem in the last chapter, as there, we were modelling the total duration of unemployment and were not dichotomising the sample, but here such small numbers mean that our ability to draw sound statistical conclusions is limited. It would be possible to improve the situation marginally if we combined the Galway sample of unemployed with that from Waterford, but the increase in numbers, particularly among women is marginal (we would have 53 rather than 33 cases for analysis). The lack of cases seriously impacts on the extent of prediction and as we will see in the results section we are more successful at predicting outcomes for men than we are for women.

This problem is further exacerbated if we attempt to use the variables collected as part of the Follow-up Survey as non-response (see Chapter 4) meant that the number of cases available for analysis using the Follow-up data is reduced even further. As explained in Chapter 4, this 'attrition' was also most pronounced among the more advantaged groups who were more likely to have short-term stays and so the numbers of short-term cases available for analysis is prohibitively low. Of the 1,083 respondents who gave answers to the Follow-up Survey, only 906 are available for analysis due to missing data on some important questions (in the Follow-up Survey). This leaves us 28 cases who were short term on the Register, 12 men and 16 women. Unfortunately, these numbers cannot support a model even if reweighted, thus in this chapter we are confined to simply using the data from the Original sample and the Register data.

5.3 The Nature of Outcome Prediction

The type of outcome prediction described in this chapter is rather different from the modelling exercise attempted in the last. Aside from the fact that we are modelling long-term stays on the Register, we are also more interested in prediction of outcomes than gaining significant effects for variables. The essential difference is that in the last chapter we wanted to *understand* the processes involved whereas here we are more concerned to extract as much *predictive* ability from the data as we can. This may sound more like a philosophical

difference (and to a certain extent it is), but in practice it means that we are less interested in finding statistically significant estimates (as reviewed in the last section of the last chapter) and more interested in quantifying the predictive ability of each variable, even if it is not statistically significant. Of course, underlying these models are real processes which lead people to become long-term unemployed/on the Register and a better understanding of these can only assist prediction, but statistically speaking, it is possible for coefficients to not be significant, but the variable to still contribute to prediction. Given this, here we use a different modelling stratagem to that used in the last chapter. We first create a ‘base model’ made up of variables representing age, sex, marital status and children and establish the extent to which this predicts the probability of being long-term unemployed.

The choice of these variables is not *ad hoc*. As well as being useful predictors of unemployment duration (see the last two chapters), they are also variables that are currently collected for the Live Register and so are readily available without additional administrative work. This means that, in principle, if this model cannot be bettered, a profile could be established using current practices. It is unlikely that this is true however, so we will also be adding other variables, as listed in the last chapter to this base model and assessing for each its contribution to prediction. This will allow us to quantify the explanatory potential of each and thus order them in terms of importance. Given that collecting information presents costs (in terms of interview time and data entry), this grading of predictive ability will allow us to define the marginal value of each additional variable.

In the following section we present tables that list the contribution of each variable (using the Galway Register Data alone) to both explained variance (a statistical measure of the success of the model) and the prediction of individual outcomes. The model we will be using is called a logistic regression which models the probability that a person will be long term on the Register rather than not⁷ (for more detail on the model used please see the Appendix to this chapter). The variables are listed in terms of their proportionate success in prediction.

5.4 Model Results

Before reviewing the effectiveness of the models used for prediction in the next section, we first examine the results of the models in terms of the factors that influence remaining on the Register for more than 12 months. If we turn first to the model for men we find results very similar to those found in the last chapter

⁷ It does this by modelling the log of the proportion of the sample becoming long-term on the Register (12 months or more) divided by the proportion who do not conditional on a set of ‘covariates’ or variables listed in the last chapter (that is $\log(p/1-p)$).

when examining durations overall. As shown in Chapter 4, age is a very important factor with those in older age groups far more likely to remain long term on the Live Register. The effect of age increases for each older age group: those aged between 25 and 34 years are 2.7 times more likely to remain long term on the Register than the youngest group (less than 25 years); those between 35 and 44 years are 3.8 times more likely; those between 45 and 54 years are 4.7 times more likely and there is a particularly large effect for those aged 55 years or more who are almost 17 times more likely to remain on the Register long term.

As we found before, those with lower levels of education are more vulnerable, although the difference is only significant for those with less than a Leaving Certificate (compared to those with Tertiary education). Those with Primary education alone are 6.4 times more likely to remain long term on Register and those with a Junior Certificate 2.9 times more likely. On the other hand, those men with a car are less than 50 per cent as likely as those without to remain long term.

Although other variables are not significant (using a 95 per cent level of statistical confidence), it is interesting to see that many of the variables have effects in the expected direction. For example, having 3 or more children increases the likelihood of being long term as does having experienced a CE, SES or Jobs Initiative course. In the opposite fashion, having a licence, being willing to move and having access to public transport all decrease the probability.

Among women we find far fewer variables significant, although the pattern of effects is roughly similar. Although age is not significant, older age groups are more vulnerable as among the men. The effect for the education variables are significant, again with effects of a similar magnitude as among the men. Those with a primary education alone are 7 times more likely than those with a tertiary education to remain long term and those with a Junior Certificate are 2.6 times more likely. Overall however, the models for women are less successful.

Finally, we estimated a model for both men and women that was designed to improve analyses by providing more cases for the models to estimate from, but in essence what we see in this model is an average of the male and female results. As such we again see significant affects for older age groups, although in the combined model the effects of being in the oldest age group are tempered to a large degree. Interestingly, the larger sample also produces a slightly lower effect for primary education alone than was found in male and female models individually, although the effect is still large with this group having over 6 times the chance of those with a tertiary qualification of being on the Register long term. As this is a combined model we needed to have a variable in the model which represented being female and this proved a significant positive influence on remaining long term with women 1.5 times more likely than men to remain on the Register after 12 months.

As discussed in the last chapter, as a very small proportion of the sample (around 6 per cent) left the Register before 12 months, it may give us more confidence in our results if we generate a larger sample by combining the Galway and Waterford data. Using this approach and estimating exactly the same models we found very similar results, although the size of the affects was reduced as would be expected when using a larger sample (and as seen in the combined male and female model for Galway). As we would expect we also saw more variables becoming significant in the combined file with being married for men proving to be a positive influence on the chance of staying long term (i.e. making it more likely) and the motivational question (would you be willing to move for a job?) becoming a significant negative influence for both men and women, as we had hypothesised in the last chapter.

The question is however, how effective were these variables at predicting the actual experience of individuals in the Galway file in terms of the probability of remaining on the Register long term?

5.5 Prediction Results

In this section we report the results of the models in terms of their effectiveness at predicting whether a specific individual would remain on the Register for more than 12 months. As described in the last section, the models we have estimated all produce ‘coefficients’ which express the impact that a specific characteristic such as being aged 55 years or more, or being married has on the probability of being long-term on the Register. Given this we can calculate an estimated probability for each individual based on their characteristics by simply adding together the coefficients (in the column labelled estimates in the Tables in the Appendix to this chapter) that apply to that individual.

Doing this we derive a probability for each, that once dichotomised can be used to predict whether a specific individual will remain long term on the Register. Of course predicting within the Galway data is not our aim, but the coefficients derived here can also be applied to other individuals to produce a prediction of their own outcomes.

Before we can decide on which factors should be selected to act as predictors of being on the Register long term we need first to establish how effective each is as a predictor so that the marginal value of collecting information on this factor can be assessed. If we can quantify the contribution of each factor to the success of the prediction then we will be in a better position to be able to recommend which should be included in the final profile of those on the Register.

The proportion of cases correctly predicted as being either short or long term (less than 12 months and 12 months or more) on the Register is given in Table 5.1. In all of the tables used here, we predict that an individual will be long term if the probability that they will be rises to 85 per cent or more. This threshold may be

raised or lowered, but at lower levels the model correctly predicts only a small minority of those who did not actually become long term, whereas at higher levels the proportion predicted as being long term becomes substantially lower than that actually observed. Choosing the cut off is thus a matter of balancing the extent to which the model either under or over predicts, although it should be remembered that in our current sample, far more individuals became long term and thus the cost of under predicting (i.e. failing to identify those who will become long term) is far more than failing to identify those who actually left the Register before 12 months. Choosing the threshold value is thus a matter of maximising the number correctly predicted by the model and this will vary from sample to sample. As the 'flow' sample of the real Register will have a far lower proportion that become long term, this threshold will have to be adjusted with experience of flow samples.

Table 5.1 which looks at the success of the model for men, shows that the 'base model' (sex, age group, marital status and children) correctly predicts almost 74 per cent of those who became long-term unemployed and 71 per cent of those who left the Register before 12 months. Overall however, this represents a success rate of around 74 per cent. If we include all of the variables in the model we see the success of the model in predicting short-term stays increases to almost 75 per cent and the rate of success in predicting long-term stays increases to 85 per cent. This means that our success rate overall increases to around 84 per cent.

Table 5.1: Proportion of Those Observed Short and Long Term On Register Correctly Predicted and Proportionate Improvement Over Base Model (Men)

	Proportion of True Short Term Correctly Predicted	Proportion of True Long Term Correctly Predicted	Proportionate Improvement Over Base Model	
			ST %	LT %
Full Model	74.51	84.39	5.55	14.52
Base Model	70.59	73.69		
Education	76.47	81.94	8.33 ¹	11.20 ¹
Rural	72.55	77.37	2.78 ³	4.99 ⁵
Literacy Problems	74.51	76.81	5.55 ²	4.23 ⁸
Participated in SES or CE	64.71	79.82	-8.33 ⁴	8.32 ⁴
Have Car	74.51	77.03	5.55 ²	4.53 ⁶
Have Licence	60.78	81.05	-13.90 ⁶	9.99 ²
Live on Bus Route	72.55	76.92	2.78 ³	4.38 ⁷
Would Move for a Job	62.75	79.93	-11.11 ⁵	8.47 ³

Numbers in superscript are the rank of the variable in its contribution to positive prediction.

In terms of variables predicting short-term stays, Table 5.1 shows that education, literacy and location are the best predictors. Education is also the primary factor predicting long stays, with having a driving licence and the motivational question following close behind. Statistically however, variables are best assessed in

terms of their contribution to the ‘explained variance’ in the model using what is known as the Log-likelihood. A table giving the Log-Likelihoods for male and female models are given in Table A5.4 in the Appendix to this chapter. If we use this approach the education variable does indeed add most to explanation with being prepared to move for a job contributing the next highest amount of variance followed by whether the man has literacy problems. Having a driving licence actually contributes the least explanatory power using this measure.

For the female model in Table 5.2 we see that the base model is worse at predicting both long (around 67 per cent) and short stays (58 per cent) than the male model. Overall, this means that the female base model only correctly identifies around two-thirds of respondents. Although the full-model improves on this overall, it still only increases the overall rate of predictive success to 73 per cent compared to 84 per cent among the men.

Table 5.2: Proportion of Those Observed Short and Long Term On Register Correctly Predicted and Proportionate Improvement Over Base Model (Women)

	Proportion of True Short Term Correctly Predicted	Proportion of True Long Term Correctly Predicted	Proportionate Improvement Over Base Model	
			ST %	LT %
Full Model	63.64	72.85	10.52	9.27
Base Model	57.58	66.67		
Education	54.55	73.95	-5.26 ⁴	10.92 ²
Rural	57.58	73.95	0.00 ³	10.92 ²
Literacy Problems	57.58	67.55	0.00 ³	1.32 ⁴
Participated in SES or CE	57.58	66.67	0.00 ³	0.00 ⁵
Have Car	57.58	66.67	0.00 ³	0.00 ⁵
Have Licence	60.61	71.08	5.26 ²	6.61 ³
Live on Bus Route	63.64	65.78	10.52 ¹	-1.33 ⁶
Would Move for a Job	48.48	77.04	-15.80 ⁵	15.55 ¹

Numbers in superscript are the rank of the variable in its contribution to positive prediction.

Among the variables in the female model, the ‘transport’ variables are most successful at predicting short-term stays, whereas the motivational question, education, location are found to be important at predicting long-term stays. If we look at their contribution to explained variance, education, the motivational question and living on a main bus route are the most important variables with having attended CE, level of literacy and having a car least explanatory.

In the full model which includes both men and women we find results which are somewhere in between those for each sex with the base model explaining roughly 60 per cent of short stays and 73 per

cent of long stays. These are improved in the full model to 69 per cent of short stays and 78 per cent of long. For short stays, level of education, living on a bus route, having a car and location all prove positive, whereas for long stays having a car licence, education and literacy problems prove to be most effective.

Table 5.3: Proportion of Those Observed Short and Long Term On Register Correctly Predicted and Proportionate Improvement Over Base Model (Men and Women)

	Proportion of True Short Term Correctly Predicted	Proportion of True Long Term Correctly Predicted	Proportionate Improvement Over Base Model	
			ST %	LT %
Full Model	69.05	77.7	16.01	7.14
Base Model	59.52	72.52		
Education	70.24	79.04	18.01 ¹	8.99 ²
Rural	61.9	75.04	4.00 ³	3.47 ⁵
Literacy Problems	58.33	76.22	-2.00 ⁵	5.10 ³
Participated in SES or CE	60.71	74.81	2.00 ⁴	3.16 ⁶
Have Car	61.9	75.04	4.00 ³	3.47 ⁵
Have Licence	53.57	80.81	-10.00 ⁶	11.43 ¹
Live on Bus Route	64.29	73.33	8.01 ²	1.12 ⁷
Would Move for a Job	58.33	76.07	-2.00 ⁵	4.90 ⁴

Numbers in superscript are the rank of the variable in its contribution to positive prediction.

These results suggest that the models we have developed so far are quite successful at predicting outcomes, although it should be remembered that these results will still need to be applied to the Waterford sample in the next chapter. The basic model of sex, marital status, age and children is already a quite effective model, but this can be substantially improved by adding other variables, although the effectiveness of the variables differ in models for men and women. Across both sexes, level of education is very important as is the transport the person has available, but for men having a car is important, whereas for women the availability of public transport is a more effective predictor.

At this stage it would be very useful to also apply the variables from the Follow-up Survey to the model to investigate whether our success in predicting outcomes can be improved using variables for the health of the person, their experience of unemployment and their experience of caring and whether they have ever worked. Unfortunately, as we saw in the last chapter, the move to modelling long-term stays on the Register is not possible with the Follow-up sample as the attrition in the sample decreases variability in the sample to such an extent that effects for a number of important variables cannot be estimated.

In the next chapter we move to the final phase of this report and attempt to test the effectiveness of the models generated using the

Galway sample in predicting outcomes in the sample of those on the Live Register from the Waterford Region.

5.6 Conclusions

In this chapter we have begun the process of developing the profile of those on the Register, the second of the overall aims of the report. Profile development requires a different approach to analysis than that adopted in the last chapter where we were simply trying to understand the factors that were important in determining the length of time that people remained on the Register. There we were interested in the whole distribution of durations, whereas for profile development we actually need to understand the factors that determine whether a person will remain on the Register for more than a year – that is, become long-term unemployed. Given this we adopted a different modelling methodology, the logistic model to examine the probability of staying long term on the Register. But profiling also demands that we are able to *predict* outcomes for individuals as well as *explain* them, thus here we used the estimated models to develop predictions for each individual, based on the model that could be compared to their actual experience. It may be unusual to rely on predictions from a model when we have the actual outcomes, but the predictions we derive may also be applied to other individuals who have not been modelled. These predictions may thus be used to generate a profile of the future experience of unemployed individuals amongst the general public. Although data is not available on the general public with which to test the profile, data is available from the Waterford Region that will be used in the next chapter to test the efficiency of the profile.

Examining the predictive success of the variables used in this chapter we found that most added value in terms of predicting outcomes, although some more than others. It was clear that the basic model of sex, marital status and children was very successful, but among both men and women education and age play a crucial role in staying long term on the Register. Available transport is also important, but in different ways for men and women with access to a car being more important for men and public transport being more important for women. For both men and women being in a rural area also proved useful for predicting outcomes as did having literacy problems, but only for men. Having previously experienced CE or SES did not aid prediction for women, but was useful for predicting long-term stays among men.

APPENDIX 5

In this chapter logit models of the probability of being long term on the Register are used.

Table A5.1: Parameter Estimates and Significance of Variables Predicting Durations of 12 Months or More on the Live Register (Logistic Regression) (Men without Follow-up Variables)

Variable	Estimate	t-statistic	Significance
Invited for EAP Interview	1.82	5.96	***
Interviewed Under EAP	0.57	1.34	n.s
Aged 25-34 years	1.00	3.44	**
Aged 35-44 years	1.33	3.33	**
Aged 45-54 years	1.55	3.22	**
Aged 55+ years	2.83	3.59	***
Married	0.74	1.84	n.s
Separated/Div/Widowed	0.18	0.32	n.s
1 or 2 Children	-0.23	-0.4	n.s
3+ Children	0.77	1.04	n.s
Primary Education	1.85	4.29	***
Junior Certificate	1.05	2.98	**
Leaving Certificate	0.38	1.13	n.s
Rural	0.32	0.93	n.s
Literacy Problems	-0.10	-0.28	n.s
Participated in SES or CE	0.63	1.68	n.s
Have Car	-0.83	-2.6	**
Have Licence	-0.05	-0.17	n.s
Live on Bus Route	-0.19	-0.55	n.s
Would Move for a Job	-0.12	-0.48	n.s
Constant	-0.65	-1.3	n.s
Log-Likelihood		-272.07585	
N of Cases		948	

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

**Table A5.2: Parameter Estimates and Significance of Variables
Predicting Durations of 12 Months or More on the Live
Register
(Logistic Regression)
(Women without Follow-up Variables)**

Variable	Estimate	t-statistic	Significance
Invited for EAP Interview	0.97	2.12	*
Interviewed Under EAP	-0.17	-0.34	n.s
Aged 25-34 years	0.16	0.41	n.s
Aged 35-44 years	0.36	0.73	n.s
Aged 45-54 years	0.73	1.26	n.s
Aged 55+ years	0.11	0.15	n.s
Married	0.11	0.24	n.s
Separated/Div/Widowed	-0.30	-0.53	n.s
1 or 2 Children	0.16	0.27	n.s
3+ Children	0.18	0.22	n.s
Primary Education	1.96	2.77	**
Junior Certificate	0.95	2.00	*
Leaving Certificate	0.15	0.44	n.s
Rural	-0.01	-0.01	n.s
Literacy Problems	-0.87	-1.53	n.s
Participated in SES or CE	0.00	0.00	n.s
Have Car	0.28	0.69	n.s
Have Licence	-0.13	-0.37	n.s
Live on Bus Route	-0.71	-1.60	n.s
Would Move for a Job	-0.44	-1.21	n.s
Constant	1.55	2.37	*
Log-Likelihood		-171.25357	
N of Cases		486	

Key: n.s: Not Significant *: $P > 0.05$ **: $P > 0.01$ ***: $P > 0.001$

Table A5.3: Parameter Estimates and Significance of Variables Predicting Durations of 12 Months or More on the Live Register (Logistic Regression) (Men and Women without Follow-up Variables)

Variable	Estimate	t-statistic	Significance
Invited for EAP Interview	1.42	5.77	***
Interviewed Under EAP	0.16	0.54	n.s
Female	0.40	2.12	*
Aged 25-34 years	0.64	2.84	**
Aged 35-44 years	0.94	3.21	**
Aged 45-54 years	1.19	3.39	**
Aged 55+ years	1.45	2.98	**
Married	0.53	1.92	n.s
Separated/Div/Widowed	-0.04	-0.09	n.s
1 or 2 Children	-0.06	-0.14	n.s
3+ Children	0.48	0.9	n.s
Primary Education	1.81	5.07	***
Junior Certificate	0.85	3.21	**
Leaving Certificate	0.23	1.01	n.s
Rural	0.09	0.38	n.s
Literacy Problems	-0.31	-1.03	n.s
Participated in SES or CE	0.42	1.48	n.s
Have Car	-0.33	-1.37	n.s
Have Licence	-0.05	-0.25	n.s
Live on Bus Route	-0.41	-1.6	n.s
Would Move for a Job	-0.23	-1.11	n.s
Constant	0.14	0.37	n.s
Log-Likelihood		-464.16168	
N of Cases		1434	

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

Table A5.4: Log-Likelihood and Percentage Change in Log-Likelihood with the Addition of Variables to the Base Model

	Men		Women	
	LL	Δ % LL	LL	Δ % LL
Base Model	-302.398	%	-182.806	%
Education	-279.433	7.59	-174.958	4.29
Rural	-297.891	1.49	-181.926	0.48
Literacy Problems	-297.163	1.73	-182.796	0.01
Participated in SES or CE	-297.977	1.46	-182.802	0.00
Have Car	-297.691	1.56	-182.796	0.01
Have Licence	-299.106	1.09	-182.574	0.13
Live on Bus Route	-298.803	1.19	-180.298	1.37
Would Move for a Job	-297.085	1.76	-180.122	1.47

6. APPLYING THE PROFILING VARIABLES IN WATERFORD – A TEST

6.1 Introduction

We are now close to achieving both the aims that we set out to accomplish at the beginning of this report: first to understand the factors which determine durations on the Live Register and second to use this information to design a profile which can be used to select those customers who are likely to become long-term unemployed. The last chapter used data from the Galway Region to model the factors implicated in long stays on the Live Register and found that a number of variables were important in predicting which individuals would experience this outcome. Our final models were quite successful at predicting individual outcomes with the model for men correctly predicting almost 85 per cent of all those who did experience long-term unemployment and around 75 per cent of those who did not. Predictions among women we were less successful, but we still managed to correctly predict almost 73 per cent of those women who stayed on the Register for 12 months or more and 64 per cent of those who left before a year. This is quite a high level of success, but the real test of whether these variables will be useful as part of a profile is to test them on data that was not used for the development of the models – that is apply the coefficients estimated in Galway to another sample and examine the level of prediction attained. Fortunately, we do have such data in the form of a sample of customers from the Waterford Live Register, as discussed in Chapter 2. These data were collected in an identical fashion to those in Galway except that no Follow-up Survey was carried out in Waterford. The absence of Follow-up Survey data for Waterford means, of course, that we will not be able to examine the effectiveness of those variables from the Follow-up Survey in Galway, namely health, experience of unemployment, full-time caring and never having worked, variables that were examined in the last two chapters, but we can test the predictive efficiency of the models generated using Galway data in Waterford.

The introduction of data from another location raises a difficult issue in profiling. Should a profile be applied nationally within

Ireland it will have to be able to predict outcomes for individuals in widely differing locations where labour markets may be very dissimilar which may impact on the efficiency of the profile. This effect may simply be to slow down all exits from the Register, making a higher proportion of the population in a particular location likely to be long term on the Register. If so, this is not particularly complex and can be dealt with easily. If on the other hand there are some individuals with particular characteristics who either find it easier or harder to leave the Register in certain locations (that is there is an 'interaction' effect between certain locations and particular characteristics), this will be far more difficult to deal with. If the profile is to be applied nationally this should be preceded by a national analysis which attempts to quantify the labour market conditions in different areas so that this can be integrated into the profile.

In this chapter we need only to be concerned with the performance of the predictive model in Waterford. In the next section we outline the methodology used before moving onto the results of the models in the third section of the chapter. In the fourth we show the success of the models in predicting outcomes for individuals. In the last section we try to draw out some conclusions from the chapter.

6.2 The Methodological Approach

The last chapter developed a model of remaining long term on the Unemployment Register in the Galway Region that predicted outcomes for individuals by generating an estimate of the affect that different characteristics had on the probability of leaving. These models were very successful, correctly predicting the outcomes for the majority of individuals, but this is unsurprising to a certain extent since the model was developed with reference to the underlying data. Certain variables were chosen precisely because we knew that these would be useful predictors and unsuccessful predictors were excluded. Similarly, the coefficients were generated internally, from the data, rather than being generated externally and then applied. A true test of the predictive ability of the model would be to apply the coefficients derived from one set of data 'blind' onto another and then examine the extent to which they predicted outcomes for completely different individuals whose experiences and characteristics had not been used to originally estimate the coefficients. Fortunately, we have just such a data set in the form of the Waterford Region Live Register Survey.

In this chapter we take the model estimated using the Galway region data and apply the coefficients derived directly onto the Waterford sample. We then compute a predicted 'probability' for each person that they will remain on the Register for more than a year and compare this to their actual experience.

6.3 Model Results

Before we move on to the success of the Galway model in predicting the outcomes for each individual in Waterford, it is useful first to examine the results from models applied directly to the Waterford sample since these will highlight differences between the two samples and alert us to reasons why the Galway results may not be entirely successful at predicting Waterford outcomes. As in the last chapter we apply logistic regressions for men, women and both combined estimating the probability that the person will remain on the Register for more than a year. The full models with diagnostic statistics can be found in the Appendix to this chapter, but here we will simply describe the outcomes of the models, as this will provide a context within which we can understand the relative success of the prediction phase in the next section.

The models for Waterford and Galway differed substantially in several important respects. First and foremost the importance of age group among men in Galway was not replicated in Waterford men. Although older age groups had a greater chance of becoming long-term unemployed, the effects were not significant and unlike Galway, were not graduated with the older groups being more disadvantaged than the younger. This suggests that age does not differentiate as well among men in Galway and this will have significant implications for the level of prediction possible. Similarly, the very strong education effect which we saw in Galway was not found in Waterford, although there is a strong positive effect for having Primary education alone (i.e. this increases the probability of long-term stays). The lack of effect for age and education among men suggests that the Waterford sample are significantly different and it will be more difficult to predict those experiencing short stays on the Register, this being more effectively predicted in Galway by the education variable.

There were similarities between the samples, however, with having a car being a very significant determinant of not staying long term on the Register, as in Galway. In Waterford however, the effect of having a car was more than twice as important as in Galway either suggesting that the unemployed in Waterford needed to travel further to work, or that there was less provision of buses in Waterford. Interestingly however, having a driving licence had a positive effect on staying long term on Register, contrary to expectations. Lastly, the motivation of men in the Waterford Region seemed to have a greater effect than in Galway with being prepared to move for a job (whether they actually did is not known) having a strong negative impact on staying long term.

For women the models for the two regions are also quite dissimilar, although unlike the male model, age group had a graduated effect, although, as in Galway the coefficients were not significant. Similarly, having a Primary education alone was almost significant and had a positive effect as in Galway. Unlike in Galway, having children in the Waterford Region made the woman less likely

to experience a long-term stay on the Register as did having a car, though neither was significant.

These results suggest that we should find the models for Waterford less predictive than those for the Galway Region. It is to the predictive models that we now turn in the next section.

6.4 Applying the Predictive Model to Waterford Region

In applying the predictive model from Galway to the individuals we use essentially the same procedure that was used with the Galway data. That is, we apply the estimated coefficient for each characteristic to the individual and then compute the probability that the person will remain long term on the Register before comparing this computed estimate to the actual, observed outcome. We can then compute the proportionate success of the Galway model in predicting outcomes in Waterford.

Surprisingly, among women in Waterford we actually find that the Galway coefficients produce a higher level of predictive success for long-term stays than in Galway with 77 per cent being correctly predicted compared to 73 per cent in Galway. For short-term stays on the other hand the outcome is less successful with only 40 per cent of short-term stays being correctly predicted. Part of this failure to predict short stays is undoubtedly due to the small number of women available for analysis in the Galway data which makes the estimates less than robust and subject to higher levels of error. Overall however, the tendency to predict long-term stays (which are far more common) means that the female model in Waterford Region is quite effective overall with a predictive success rate of close to 76 per cent compared to 72 per cent in Galway.

For men, the application of the Galway estimates produces quite similar results as for women with 71 per cent of long-term stays being correctly predicted and 46 per cent of short-term stays. These results are lower than for the Galway male sample where 84 per cent of long- and 75 per cent of short-term stays were correctly predicted, although this result is unsurprising given the different patterns found in the Waterford data even for the 'base mode' variables. Overall however, we still manage to correctly predict almost 70 per cent of the actual outcomes in Waterford (compared to 84 per cent in Galway).

6.5 Conclusions

Our brief overview of the results for Waterford in this chapter show that the models created for the Galway data are not as effective at predicting outcomes in Waterford, but the results are still very encouraging. The lower level of success appears to be because the main variables such as age and education do not seem to have as much purchase in Waterford, particularly among men, although it is not clear why this is the case. If such variables do not influence outcomes this is usually because there are so few jobs that none of the unemployed are being re-employed, but we know this not to be true in Waterford since the long-term unemployment rate in the

Region was actually lower than in Galway at the time of sample selection. Given this, it may be that the sample selection itself in Waterford differs in some way from that in Galway.

However, in spite of the large differences between the Regions in terms of the effects in the models, the prediction rate for Waterford using the Galway model was still significant. The low proportion of both the Galway and Waterford samples who were short-term unemployed means that the models were always going to be better at predicting long-term stays (the model initially works from the observed proportion) and so the overall prediction rate should be discounted somewhat compared to the models ability to predict short-term stays. Only 46 per cent of short-term stays were correctly predicted in the male model and only 40 per cent in the female model, although this could be substantially improved, we would suggest with a larger sample. It would also be possible to increase the proportion of the short-term unemployed correctly predicted by increasing the threshold probability for the Waterford sample (from the 85 per cent used in Galway), but this would also decrease the proportion of long-term stays correctly predicted and thus the overall success rate.

APPENDIX 6

The models used in this chapter are identical to those used in the last in all respects except data from Waterford region rather than Galway Region.

Table A6.1: Parameter Estimates and Significance of Variables Predicting Durations of 12 Months or More on the Live Register

**(Logistic Regression)
(Men without Follow-up Variables)**

Variable	Odds	t-statistic	Significance
Invited for EAP Interview	-0.05	-0.2	n.s
Interviewed Under EAP	0.59	1.24	n.s
Aged 25-34 years	-0.48	-1.59	n.s
Aged 35-44 years	0.40	0.98	n.s
Aged 45-54 years	0.75	1.54	n.s
Aged 55+ years	0.34	0.66	n.s
Married	0.76	2.11	*
Separated/Div/Widowed	0.86	1.61	n.s
1 or 2 Children	-0.02	-0.07	n.s
3+ Children	0.43	0.71	n.s
Primary Education	0.32	0.69	n.s
Junior Certificate	-0.08	-0.18	n.s
Leaving Certificate	-0.59	-1.3	n.s
Rural	-0.33	-1.23	n.s
Literacy Problems	-0.51	-1.8	n.s
Participated in SES or CE	-0.18	-0.61	n.s
Have Car	-1.72	-5.04	***
Have Licence	0.86	2.7	**
Live on Bus Route	-0.30	-1.08	n.s
Would Move for a Job	-0.70	-2.89	**
Constant	2.42	4.41	***
Log-Likelihood		-296.69823	
N of Cases		847.00	

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

Table A6.2: Parameter Estimates and Significance of Variables Predicting Durations of 12 Months or More on the Live Register (Logistic Regression) (Women without Follow-up Variables)

Variable	Odds	t-statistic	Significance
Invited for EAP Interview	1.20	2.43	*
Interviewed Under EAP	-0.83	-1.47	n.s
Aged 25-34 years	0.94	1.50	n.s
Aged 35-44 years	1.26	1.84	n.s
Aged 45-54 years	1.28	1.59	n.s
Married	0.50	0.84	n.s
Separated/Div/Widowed	1.61	1.01	*
1 or 2 Children	-0.89	-2.02	n.s
3+ Children	-0.67	-0.89	n.s
Primary Education	1.27	1.30	n.s
Junior Certificate	0.01	0.01	n.s
Leaving Certificate	0.31	0.47	n.s
Rural	0.58	1.28	n.s
Literacy Problems	0.23	0.29	n.s
Participated in SES or CE	-0.93	-1.72	*
Have Car	-1.44	-2.58	n.s
Have Licence	-0.12	-0.27	n.s
Live on Bus Route	0.21	0.52	n.s
Would Move for a Job	-0.75	-1.51	*
Constant	1.92	2.20	***
Log-Likelihood		-113.13001	
N of Cases		497	

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

Table A6.3: Parameter Estimates and Significance of Variables Predicting Durations of 12 Months or More on the Live Register (Logistic Regression) (Men and Women without Follow-up Variables)

Variable	Odds	t-statistic	Significance
Invited for EAP Interview	0.44	1.93	n.s
Interviewed Under EAP	-0.05	-0.15	n.s
Female	0.95	4.31	***
Aged 25-34 years	0.02	0.06	n.s
Aged 35-44 years	0.67	1.98	*
Aged 45-54 years	0.81	1.98	*
Aged 55+ years	0.85	1.79	n.s
Married	0.74	2.59	*
Separated/Div/Widowed	0.82	1.73	n.s
1 or 2 Children	-0.36	-1.42	n.s
3+ Children	0.06	0.13	n.s
Primary Education	0.66	1.67	n.s
Junior Certificate	-0.02	-0.05	n.s
Leaving Certificate	-0.17	-0.47	n.s
Rural	-0.06	-0.25	n.s
Literacy Problems	-0.37	-1.38	n.s
Participated in SES or CE	-0.43	-1.7	n.s
Have Car	-1.44	-5.33	***
Have Licence	0.43	1.77	n.s
Live on Bus Route	-0.06	-0.24	n.s
Would Move for a Job	-0.82	-3.89	***
Constant	1.75	3.81	***
Log-Likelihood		-411.40343	
N of Cases		1,373.00	

Key: n.s: Not Significant *: P>0.05 **: P>0.01 ***:P>0.001

7. SUMMARY AND CONCLUSIONS

7.1 Active Labour Market Policy in Ireland

In the last eight years or so economic development in Ireland has seen unemployment fall dramatically from around 16 per cent in 1994 to less than 4 per cent by 2001. Even though the rate has increased since 2001, levels of unemployment at the time of writing are still extremely low in historical perspective. Unemployment may no longer be the huge problem that it was to Irish society, but for each individual unemployed it can still present a personal crisis that can severely affect their living standards and future prospects. Because of this, governments have an obligation, both from a stand point of expenditure efficiency and individual social welfare to help the unemployed get back into work. Ireland actually has a very well developed system of ‘active labour market policies’ – training and subsidised employment for the unemployed that has helped many thousands of individuals back into work and for the last seven years has been operating the National Employment Action Plan (NEAP). The NEAP was first instituted on September 1st 1998 at which point all young people aged under 25 years who had reached six months on the Register were referred by the (then) Department of Social, Community and Family Affairs to FÁS for interview. From 1st March 1999, all persons under 25 years who reached 18 months on the Register were referred, as were those aged 25-35 years approaching 12 months on the Live Register from May 1st onward. In February 2000 the process was extended to the remaining group aged 35-54 years as they became unemployed for 12 months or more. From the evidence that is available (although NEAP has not yet been systematically evaluated) this process seems to have been very successful and suggests that a more proactive approach to the unemployed is beneficial. Yet, at the earliest, the NEAP only intervenes after a person has been on the Live Register for six months, and for most groups this period is a year at which point research suggests they and their future prospects will already have been permanently scarred by the experience.

This would suggest that earlier intervention still would be advantageous, but of course intervening with all persons on the Live Register as soon as they sign on may not be very efficient (and certainly would be very expensive) since a large proportion will leave the Register for employment in a relatively short time without any help or intervention. In this sense, policy really need only be

concerned about those coming onto the Register who will become long-term unemployed and who will require help to find employment. The tricky question is how to identify these people?

7.2 Identifying Those at Risk of Long-Term Unemployment

It would be possible to attempt to select those people at risk of long-term unemployment by looking for a particular characteristic such as being over an age threshold, or having low education, but such ‘characteristic screening’ is rather inflexible and inaccurate. A more flexible approach would be to interview the unemployed and make a decision on their need for intervention based on the assessment of a trained official, but as argued in the first chapter of this report, this approach has the drawback that it is unsystematic and liable to incorrect judgements since different officials may use different rules or interpret preset rules differently. Instead, this report has advocated the development of a ‘profiling’ approach to the early identification of the long-term unemployed.

Rather than rely on single characteristics or the decisions of officials, a profiling system of selection is based upon the systematic evaluation of multiple characteristics whose impact on the probability of becoming long-term unemployed have been assessed using statistical evidence. This report has detailed the development of such a profile using data drawn from random surveys of those on the Live Registers of the Galway and Waterford Regional Offices of the DSFA in 2000 and information on the same people drawn from the Live Registers themselves. The report had two main aims: first to understand the processes that lead to exit from the Live Register and the impact of particular personal characteristics and second to use this information to develop a practical profiling system.

Chapter 3 began the process of understanding the impact of various characteristics on the duration of unemployment, as measured using Live Register data, using basic bivariate techniques. Though simple these analyses showed clearly that factors such as age and level of education were very powerful predictors of remaining on the Live Register for a longer period. The older the unemployed person, the less quickly they left the Register to employment. Similarly, each extra level of educational qualification had the effect of shortening the period on the Register on average and increasing the probability that the person would become employed. These results are very much in line with previous research and underline the importance of age and education. However, the development of a profile requires that we investigate the impact of a range of variables on the probability of remaining on the Register for an extended time, and moreover evaluate the independent affect of each. To do this we need to use multi-variate statistical techniques, which was the subject of Chapter 4.

Chapters 3 and 4 show clear evidence using sophisticated statistical models that education has a significant role in longer spells on the Register. The lower the level of education of the respondent,

the less likely it is that they will leave the Register to employment a pattern common to both men and women. For men, age was also a significant factor, with men in older age groups finding it more difficult to find employment with the corollary that older men are far more likely to move from the Live Register on to a Community Employment Scheme or move into retirement. Having a form of transport also proved very important in helping men to leave the Register to employment, whereas having a larger number of children slowed down the transition for men from the Register to employment. Chapter 4 also confirmed evidence found in previous studies that ill health and previous spells of unemployment or full-time caring also slow down exit from unemployment. These effects were very pronounced and suggest that these variables are very important in determining outcomes.

These results suggest a very structured relationship between particular characteristics and duration on the Live Register, but such information needs to be translated into a format that can be used in practice in a profile to select the potential long-term unemployed. To achieve this, Chapter 5 developed a set of models predicting long-term status which used the variables identified in Chapter 4 and attempted to evaluate the ability of these models to predict outcomes in the sample. That is, what proportion of those who would go onto to become long-term unemployed can we identify at first registration using the variables in our model? This is a very practical question that will have enormous importance for the efficiency of a profiling system since large numbers of false positives (i.e. where a model predicts the person would be long term, but in reality they would be short term) would mean large 'deadweight' costs as training would be used where it was not actually needed. On the other hand, false negatives (not identifying the long term) would leave vulnerable people without intervention and on the Register for a long period.

The results in Chapter 5 on the factors predicting becoming long term on the Register underlined those of Chapter 4: the analysis of the impact of age group showed that among men the effect of age increases for each older age group: those aged between 25 and 34 years are 2.7 times more likely to remain long term than the youngest group (less than 25 years); those between 35 and 44 years are 3.8 times more likely; those between 45 and 54 years are 4.7 times more likely and there is a particularly large effect for those aged 55 years or more who are almost 17 times more likely to remain on the Register long term. Similarly for educational level, those with Primary education alone are 6.4 times more likely to remain long term than those with a tertiary qualification and those with a Junior Certificate 2.9 times more likely. Among women, the impact of age and education are similar, with those with a Primary education alone being 7 times more likely than those with a tertiary education to remain long-term. Those with a Junior Certificate are 2.6 times more likely. Overall however, the models for women were less successful.

The models in Chapter 5 proved extremely successful at predicting whether a person would become long-term unemployed,

although the models for men were more successful than those for women. The models for women were limited by the small number of cases that were available for analysis, but it also seems true that the factors behind female labour force participation are more complex than those for men. Women tend to be influenced to a far greater extent than men by domestic circumstances and the interaction of these with occupational career over their life course. Among men the model correctly predicted around 75 per cent of all short-term stays on the Register and around 85 per cent of long-term stays with an overall prediction success rate of 84 per cent. Among women the full model correctly predicted around 64 per cent of short-term stays on the Register and 73 per cent of long-term stays leading to an overall prediction rate of 72 per cent.

Although the above prediction figures are very encouraging, the models would undoubtedly have been improved if we had been able to estimate models that included variables from the Follow-up Survey such as the health status of the individual and their experience of unemployment and full-time caring in the past. Unfortunately, the structure of the data and non-response in the Follow-up Survey left us with too few cases to be able to estimate a meaningful model, but we do know from the models in Chapter 4 that these variables are important predictors of exit from the Register to both employment and other destinations. We go on to discuss the practical implementation of the profiling model and will return to the inability to estimate coefficients for these variables.

In Chapter 6 we put the models developed in Chapter 5 to the test by applying them to the Waterford Region sample of the unemployed. These data were not used in the development of the models in Chapters 4 and 5. Applying the models to data from another location is useful for assessing their wider applicability. The Waterford models were encouraging although the overall rate of prediction was lower than in Galway with the experience of around 70 per cent of all male respondents correctly predicted. The lower rate of prediction for men was true for both long- and short-term stays in unemployment, but prediction was particularly poor for short-term stays where the model predicted only 46 per cent correctly (compared to 75 per cent in Galway). Among women for long-term stays the Waterford models actually achieved a higher success rate (76 per cent) in prediction than those for Galway (73 per cent), but as with men, the models were weaker at predicting short-term stays where they achieved a very low rate of correct prediction at just 40 per cent. As with the Galway data the shortage of cases in the data which were short term on the Register in reality means that it would always be easier to predict long rather than short stays, but it was clear that the factors predicting unemployment stay were also different in Waterford compared to Galway. We did not find the same age and education affects when modelling Waterford data that we found when using Galway data and this impacted on the prediction results when we applied Galway coefficients to Waterford

7.3 Implementing Profiling

data. This suggests that any future profiling project will have to look carefully at the way in which specific individual characteristics such as age, sex and education interact with the local labour market conditions and how this can be handled in a profiling system.

The analyses in this report and most notably those in Chapter 5 provide the basic information necessary to implement a profiling process among those on the Live Register, i.e. a list of characteristics which predict the probability that the person will remain on the Register long term and ‘weights’ or coefficients for each of these characteristics. These are listed in detail in the tables in the Appendix to Chapter 5. In implementing this information, however, there are some practical considerations.

First of all, although these coefficients could be combined by hand and the probability that a person with a specific combination of characteristics becoming long-term unemployed calculated, in practice software will need to be developed which will aid those making a decision about whether this person needs intervention. Working out the probability that a person will become long-term unemployed is a simple matter of adding together the coefficients for that person’s characteristics plus the ‘constant’ from the model and then transforming this from an ‘additive’ form to an ‘exponential’ form through exponentiation or ‘anti-logging’. However, this could be done more reliably and without special training if the official making the decision or processing the information from the customer is aided by computer software. This software could be as simple as a spreadsheet with some limited programming, or a more elaborate data base with a specific user interface, but neither would require a great deal of development and could be produced cheaply and quickly, although consideration would have to be given about the training of specific staff in using the program.

When applied in DSFA offices, the ideal would be for the information from the customer to be inputted directly into the program, perhaps by the customer themselves so that the minimum of coding from questionnaires into the program is required, although this would entail the development of a user-friendly interface that all clients could manage. This would both save time and resources during the interview process and eliminate errors in transcription.

As discussed in Chapter 1, given scarce resources and limited numbers of places on programs, the resulting ‘decision’ from the software about whether an individual is above a threshold and in need of intervention should be augmented with a ranking that will allow those in most need to be given priority access. A specific combination of characteristics will provide a probability coefficient of the likelihood that a particular person will become long-term unemployed which varies between 0 and 1. The exact threshold at which an individual could be said to be in need of an intervention should remain static, but above this threshold those in need of an

intervention could be ranked by their estimated probability and the proportion sent forward for intervention varied depending on the level of resources available.

In the last section we briefly discussed the difficulties experienced in estimating effects using the variables for health status and past unemployment and caring in the Follow-up Survey. Our inability to enter these into the model means that we cannot provide a coefficient that can be used in a profile. Nonetheless, we would have to stress that evidence both from Chapter 4 in this report and from elsewhere (Layte and O'Connell, 2001; Layte and Callan, 2001) shows that these variables are very important predictors of the probability of becoming long-term unemployed. Given this we would suggest that these variables should be collected as part of the a national profiling pilot and the actual affects for these characteristics calculated using that data before a program of profiling was made fully operational. This two-step procedure would also allow more information to be collected on the impact of different locations and regions on unemployment.

7.4 Savings from Profiling

Table 7.1 presents an attempt to quantify the potential reduction in unemployment that could be achieved by implementing a profiling system to identify early those most at risk of entering long-term unemployment combined with effective active labour market programmes to enhance the employment prospects of those so identified. The simulation is based on the Live Register Age by Duration Analysis published by the CSO relating to October in each of the years 2000 to 2004. Panel A simply reports the observed pattern of unemployment by duration, and thus establishes the benchmark, without profiling.

Panel B presents a simulation in which profiling is introduced in 2000. In 2001 we observe the first result of profiling as the inflow to long-term unemployment i.e. those making the transition from less than 1 year to 1-2 years unemployment duration, falls by 30 per cent. This 30 per cent represents the average net impact of effective ALMP interventions (e.g. Specific Skills Training) derived by O'Connell (2002) in a study using follow-up data of FAS clients. The number entering long-term unemployment falls by 4,551 in 2001. In 2002, the inflow to long-term unemployment is also reduced by 30 per cent, and the number making the transition from 1-2 years to 2-3 year unemployment duration also falls, compared to the benchmark in Panel A. This latter effect is simply due to the reduction in the inflow to long-term unemployment achieved in the previous year, not to any presumed additive effect of profiling. The declines in unemployment flows accumulate over 3 years, so the full effects are observed in 2003 and thereafter. The result is a 'steady state' reduction in total unemployment of the order of about 9,500.

Table 7.1: Simulated Estimates of Potential Reduction in Unemployment and Savings in Unemployment-related Social Welfare Payments

	1	2	3	4	6	7	8
	Unemployment Duration					Total	Reduction in Unemployment
A. Actual	Lt 1 yr	1 to2yrs	2 to3yrs	3 or more	(Number)		
Oct-00	85,668	16,509	10,641	26,892	139,710		
Oct-01	96,100	15,170	6,935	23,295	141,500		
Oct-02	114,692	16,890	5,719	20,364	157,665		
Oct-03	117,803	20,123	7,347	19,302	164,575		
Oct-04	109,367	18,296	8,037	18,344	154,044		
B. With Profiling & Intervention							
Oct-00	85668	16,509	10,641	26,892	139,710		0
Oct-01	96,100	10,619	6,935	23,295	136,949	4,551	€29.6
Oct-02	114,692	11,823	4,003	20,364	150,882	6,783	€44.1
Oct-03	117,803	14,086	5,143	18,032	155,064	9,511	€61.8
Oct-04	109,367	12,807	5,626	16,827	144,627	9,417	€61.2

¹Based on Unemployment Benefit and Assistance payments in 2003.

In estimating the potential savings we have calculated the annual cost of an unemployment claim at €6,495. This is the ratio of total expenditure on unemployment supports in 2003, €1,043 million, to the total number of recipients of Unemployment Benefit and Assistance in the same year, 145,339 (Dept of Social and Family Affairs, 2003). On this basis the annual savings amount to almost €30 million in the first year of profiling, rising to a steady state of just over €60 million in the third and each subsequent year.

It should be noted that these are our best estimates based on a series of assumptions. First, we assume that a profiling system that accurately identifies those most at risk of entering long-term unemployment can be developed. The results reported in this study suggest that this is feasible.

The second assumption is of timely delivery of effective ALMPs to about 15,000 to 20,000 participants annually. On the basis of ALMP provision reviewed in Chapter 1, this level of activity is well within the numerical capability of existing provision of programmes for the unemployed, although some restructuring of the nature of programmes might be warranted.

Third, we assume that ALMPs can achieve a reduction of 30 per cent in the number of profiled individuals entering long-term unemployment. This is based on the average net effectiveness of skills training programmes found to obtain in a study that compared employment outcomes for participants in training versus non-participants and controlled for the effects of other relevant characteristics (O'Connell, 2002). Had we, pessimistically, assumed a 25 per cent, rather than 30 per cent, reduction in the inflow to long-term unemployment, then the reduction in the number unemployed would have fallen from about 9,500 to about 8,000, and the

exchequer savings from €61 million to about €51 million. A more optimistic assumption of a 35 per cent reduction in the inflow to long-term unemployment would have correspondingly increased the steady-state reduction in unemployment by 1,500 and increased saving by about €10 million. In estimating the labour market effects of ALMPs we have ignored potential displacement effects whereby successful ALMP participants obtain jobs in the labour market that might otherwise have been achieved by others. We are not aware of any reliable estimates of displacement effects of ALMPs in Ireland, but we can expect such effects to be minimal in a context of near-full employment with immigration to meet mainly low-skilled labour demand.

Finally, we have assumed that the savings can be estimated by the average value of Unemployment Benefit and Assistance per recipient. This is likely to be a conservative estimate since it takes no account of other and supplementary unemployment-related expenditures nor the possibility that the long-term unemployed may have more dependents and thus qualify for higher average payments.

7.5 A National Profile Pilot: The Importance of Location and Sample Structure

Apart from the distinction between the Galway and Waterford data in this report we have only briefly discussed the importance of local labour market conditions, but it is a very important aspect of a future-profiling programme. Different regions have different levels of unemployment and these variations in local labour markets need to be taken into account in any profile. To calculate the impact of location a national profile pilot would need to be carried out which randomly sampled individuals on the Live Register from all over the Republic of Ireland. The pilot need not carry out interventions with those taking part and in fact, having at least one sample that does not experience any interventions would be valuable since this would allow national coefficients to be generated (similar to those in Chapter 4 here) once a reasonable period had elapsed that could be compared to the coefficients in this report. Collecting a pure ‘non-intervention’ sample in Ireland is almost impossible in current circumstances as all individuals would enter the NEAP process if unemployed for a significant period of time, but as in this report, NEAP status will be known and can be controlled for in the analyses of the data.

By collecting a national sample of the unemployed it would be possible to estimate the impact of location and remove its affect from the estimate of the effect of the individual characteristics and given a large sample, say over 10,000 individuals unemployed, location effects could be generated on a county level basis. This would allow very precise estimates of the effects of different characteristics to be calculated (because of the large sample) as well as good estimates of the effect of county unemployment rates. The ideal solution would be to sample individuals on the Live Register

from all offices in the state, but this would have obvious resource implications.

One of the drawbacks of the sample used in the current report is the fact that the sample used for analysis is a 'stock' sample in that it is drawn from the stock of people on the Registers in Galway and Waterford Regions on a particular day in 2000. However, unemployment is not a stock phenomenon but rather a flow of people on and off the Register with only those with the most disadvantaged characteristics staying on the Register for long periods. The predominance of the long term in our samples limited our discussion about the processes at work and thus any national pilot should endeavour to collect a flow sample of the unemployed, i.e. a sample of people entering the Register over a longer period. The longer the period the better for the subsequent analyses, but a period of around a month should be adequate as long as this does not coincide with a particular seasonal fluctuation in the Live Register.

REFERENCES

- BLACK, D., J. SMITH, M. PLESCA, and S. SHANNON, 2003. "Profiling UI Claimants to Allocate Reemployment Services: Evidence and Recommendations for States". Final Report to US Department of Labor. Washington DC: US Department of Labor.
- BERGER, M., D. BLACK, and J. SMITH, 2000. "Evaluating Profiling as a Means of Allocating Government Services" in Michael Lechner and Friedhelm Pfeiffer (eds.), *Econometric Evaluation of Active Labour Market Policies*, Heidelberg: Physica, pp. 59-84.
- BRYSON, A., and D. KASPAROVA, 2003. "Profiling Benefit Claimants in Britain: A Feasibility Study", Leeds: Corporate Document Services.
- DWP Research Report 196. London: Dept of Work and Pension.
- DENNY, K., C. HARMON, and P. O'CONNELL, 2000. *Investing in People: The Labour Market Impact of Human Resource Interventions Funded by the Structural Funds*, Policy Research Series No. 38, Dublin: The Economic and Social Research Institute.
- DEPARTMENT OF ENTERPRISE, TRADE AND EMPLOYMENT, 2004. *National Employment Action Plan 2004 Ireland*. Dublin: Department of Enterprise Trade and Employment.
<http://www.entemp.ie/publications/labour/2004/employmentactionplan.pdf>
- DEPARTMENT OF SOCIAL AND FAMILY AFFAIRS, 2003. *Statistical Report on Social Welfare Services 2003*. Dublin: Stationery Office.
<http://www.welfare.ie/publications/annstats/03/2003stats.pdf>
- EBERTS, R., and C. O'LEARY, 2003. "A New WPRS Profiling Model for Michigan", Upjohn Institute Staff Working Paper No. 04-102.
- FROLIOCH, M., M. LECHNER, and H. STEIGER, 2003. "Statistically Assisted Programme Selection – International Experiences and Potential Benefits for Switzerland", *Swiss Journal of Economics and Statistics*, Vol. 139, pp. 311-331.
- GIBBINS, C., 1997. "Early Identification of Pilots: Results at 12 Months. Employment Service, Rep113, cited in C. Hasluck, (2004). *Targeting Services in the Individual Customer Strategy: The role of profiling. A review of research evidence*.
- HASLUCK C., 2004. *Targeting Services in the Individual Customer Strategy: The role of profiling. A review of research evidence*, Department for Work and Pensions/Jobcentre Plus.
- JOHNSON, T., 1996. "Reemployment Service Strategies for Dislocated Workers: Lessons Learned from Research," *Worker Profiling and Reemployment Services (WPRS) System: National WPRS Colloquium, 1996*. Washington D.C.: US Department of Labor, Employment and Training Administration.
- KENNEDY, B., E. BROWN, D. MCGINN, and J. GLYNN, 2001. *Survey of Unemployed Customers and Employment Opportunities*, Galway: Department of Social, Community and Family Affairs, Galway Regional Office.
- LAYTE, R. and T. CALLAN, 2001. "Unemployment, Welfare Benefits and the Financial Incentive to Work", *The Economic and Social Review*, Vol. 32, No. 2, pp. 103-129.
- LAYTE, R. and P.J. O'CONNELL, 2001. *Moving On? The Dynamics of Unemployment in Ireland in the 1990s*, Dublin: Combat Poverty Agency.
- LECHNER, M, and J. SMITH. 2003. "What is the Value Added by Caseworkers?" IZA Discussion Paper No. 728.

- MORTENSEN, D. T., 1977. "Unemployment Insurance and Job Search Decisions", *Industrial and Labour Relations Review*, Vol. 30, pp. 505-517.
- MAHER, G., T. MEEHAN, J. FALLON, and SOUTH EASTERN REGIONAL MANAGEMENT TEAM, 2001. *Waterford Live Register Survey*, Waterford: Department of Social, Community and Family Affairs, Waterford Regional Office.
- NARENDRANATHAN, W. and S.J. NICKELL, 1985. "Modelling the Process of Job Search", *Journal of Econometrics*, Vol. 28, pp. 29-49.
- NARENDRANATHAN, W. and M. STEWART, 1995. "The Determinants of Individual Unemployment Durations in An Era of High Unemployment", *Economic Journal*, Vol. 105, pp. 321-332.
- NICKELL, S. J., 1979. "Estimating the Probability of Leaving Unemployment", *Econometrica*, Vol. 47, No. 5, pp. 1249-1266.
- O'CONNELL, P. J. and F. MCGINNITY, 1997. *Working Schemes? Active Labour Market Policy in Ireland*, Aldershot: Ashgate.
- O'CONNELL, P., 2002. "Are they Working? Market Orientation and the Effectiveness of Active Labour Market Programmes in Ireland", *European Sociological Review*, Vol. 18.
- OECD, 1998. *Early Identification of Jobseekers at Risk of Long-Term Unemployment: The Role of Profiling*. Paris: OECD.
- OECD, 2004. "The Ins and Outs of Long-term Unemployment", Chapter 4 in *OECD Employment Outlook 2004*. Paris: OECD.
- PAYNE, J., B. CASEY, C. PAYNE and S. CONNOLLY, 1996. *Long Term Unemployment: Individual Risk factors and Outcomes*, London: Policy Studies Institute.
- PEDERSEN, P. J. and N. WESTERGÅRD-NIELSEN, 1993. "Unemployment: A Review of the Evidence from Panel Data", *Economic Studies* 20 (Spring). Paris: OECD.
- WANDNER, S., and J. MESSENGER, (eds.), 1999. *Worker Profiling and Reemployment Services Policy Workgroup: Final Report and Recommendations*. Working Paper, Washington DC: US Dept. of Labor.
- WELLS, B., 1998. "Early Identification/Profiling in the United Kingdom" in *Early Identification of Jobseekers at Risk of Long-term Unemployment, The Role of Profiling*, Paris: OECD.
- WHITE, M., 1983. *Long-term unemployment and Labour Markets*, London: Policy Studies Institute.