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NATIONAL PROFILING OF THE UNEMPLOYED IN IRELAND

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This paper builds on the initiative taken by Barry Kennedy and his team in the Western Region of the Department of Social and Family Affairs to investigate the possibility of developing a profiling system for the unemployed in Ireland. We would like to thank Barry Kennedy, Eoin Brown and Dave McGinn for their active engagement with and support for the project over several years. Thanks also to our ESRI colleagues Paul Gorecki and Richard Layte who reviewed an earlier draft and provided useful comments. We would also like to thank Mary Cleary, Regina Moore and Deirdre Whitaker of the ESRI for all their work in preparing the manuscript for publication.

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FOREWORD

There are many potential benefits to be derived through the introduction of a National Customer Profiling system for the unemployed in Ireland. Earlier interventions with those who need them most could shorten the duration of unemployment, thus improving the person's chances of obtaining sustainable employment and not returning to unemployment in the future. Prevention of long-term unemployment would avoid the negative social, financial, health and other associated impacts for individuals and families. In addition, there could be substantial savings in unemployment scheme costs with more efficient and effective focusing of resources and improved Live Register management.

Although the Department of Social and Family Affairs began the data capture phase of this study in September 2006, its research into employability-related issues and the pursuit of a customer profiling model goes back some years. The ESRI's report on *Employability and the Live Register* was launched by the then Minister for Social, Community and Family Affairs, Dermot Ahern, TD in May 2001.[1] That report identified the main factors associated with reduced employability, based on data from the Live Register, the Labour Force Survey of 1997 and the Living in Ireland Surveys of 1994 and 1997. The results from a study conducted by the Department of Social and Family Affairs in Galway in 2000, involving over 1,400 mainly long-term unemployed customers, were also drawn upon. The report suggested a movement towards profiling, whereby those most at risk of long-term unemployment could be identified and given immediate access to interventions which could speed transition back to employment.

Subsequent to the launch of that report the ESRI was contacted to explore whether the Department's study in Galway could be used as a basis for a longitudinal study into employability and the development of a customer profiling model. Based on those discussions, a longitudinal study was initiated and conducted in co-operation with the ESRI. The study involved a follow-up survey of the 1,400 customers interviewed in Galway in 2000, the majority of whom agreed to be re-interviewed some eighteen months later. This was a particularly difficult task as many of those involved were no longer customers of the Department and were difficult to trace. Their co-operation and voluntary participation in this follow-up were much appreciated. The data from that study, together with other administrative data were used to develop our first profiling model. The results were published in the ESRI's first report on

[1] Barrett, A., C.T. Whelan and J.J. Sexton, 2001. *"Employability" and its Relevance for the Management of the Live Register.* ESRI Policy Research Series No. 40. Dublin: Economic and Social Research Institute.

profiling, launched by the then Minister for Social and Family Affairs, Seamus Brennan, TD in July, 2005.[2] Although the accuracy of the model developed was quite high, it was clear that larger scale research, on a national basis, would be needed to develop a model accurate enough to facilitate the introduction of a national customer profiling system. Consequently, preparations commenced for the research leading to this report.

A study of this nature and size had not previously been undertaken by the Department. The fact that customer participation was voluntary required considerable dedication and commitment by front line staff to ensure the highest possible participation rates. Choosing the correct wording and sequencing of questions was also critical to the success of the customer interview process. Briefing sessions, together with detailed instructions and a help desk facility were used to share an understanding of the aim of the project and achieve consistency in approach across a network of over 100 offices and potentially involving over 1,000 staff.

Huge effort has been made to ensure the success of this project and I would like to thank all of those involved including the ESRI, the Galway project team members, the project board members, our Local and Branch office management and staff and all of the customers who voluntarily participated in this study.

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[2] Layte, R., and P.J. O'Connell, 2005. *Profiling the Unemployed: An Analysis of the Galway and Waterford Live-Register Surveys.* ESRI Policy Research Series No. 55. Dublin: Economic and Social Research Institute.

EXECUTIVE SUMMARY

Since early 2008 there has been a severe deterioration in the Irish economy, which has had knock-on implications for the labour market. Unemployment increased from about 4.5 per cent at the end of 2007 to about 12 per cent in May 2009 (Central Statistics Office, 2009). Given the scale of the problems currently facing the Irish economy, unemployment is forecast to rise considerably over the next year, and it may reach the historical highs of the early 1990s before the end of 2010. There is a marked risk that long-term unemployment will also increase over the period.

The prevention of long-term unemployment is important from both economic and social perspectives. Many of those who become long-term unemployed suffer particular labour market disadvantages, such as skill erosion and scarring, leading to difficulty in re-entering employment. In addition, long-term unemployed individuals are more likely to suffer from social exclusion and poor health. From the perspective of the wider economy, long-term unemployment entails substantial financial costs in both welfare payments and lost revenue as well as in lost production.

Over the last decade or so, many countries have begun to develop statistical profiling systems in order to identify those individuals with a high probability of becoming long-term unemployed and to refer them to appropriate labour market programmes. The method involves the use of an econometric model to assign a risk score to each claimant for unemployment benefit in terms of his/her likelihood of falling into long-term unemployment. This study reports the results of the development of a statistical profiling model for Ireland. The data used in this study comes from a specially designed survey administered by the Department of Social and Family Affairs (DSFA) to all individuals that claimed unemployment benefit between September and December 2006, who were subsequently tracked for more than one year.

The main findings of this study were as follows:

- From September 2006, and for the following three months, all new claimants on the Live Register were issued with a questionnaire developed by the Economic and Social Research Institute in partnership with the DSFA, to collect data on a range of variables that are believed to influence subsequent employment prospects. Claimants' statuses on the Live Register were then tracked over the following eighteen months by the DSFA administrative IT system, the Integrated Short-Term Scheme (ISTS). A total of 60,189 individuals made claims for unemployment between September and December 2007. After the elimination of duplicates, unsuccessful claimants and individuals failing to complete the questionnaire, the final sample used in this study consisted of 33,754 claimants. Of this sample, 59 per cent had re-entered the labour market within twelve months, with the remaining 41 per cent becoming long-term unemployed or dependent on some other social welfare payment.

- Based on this sample, and using the questionnaire data in conjunction with some information from the Live Register database, statistical profiling models of long-term unemployment were estimated for males and females separately. Both models were found to be very well specified and thus provide very accurate predictions of individuals' likelihood of entry to long-term unemployment. The accuracy of the models were found to increase substantially at higher levels of long-term unemployment risk.

- In terms of international comparisons, very few countries implementing statistical profiling release details of their models. However, comparison was possible with Denmark. The Irish model was found to provide more accurate predictions of entry to long-term unemployment than its Danish equivalent.

- Regarding the model specifics, a number of individual characteristics/attributes were found to be strongly associated with long-term unemployment risk. Specifically, the results for the male model indicate that the probability of remaining on the Live Register is associated with a recent history of long-term unemployment, previous participation on the Community Employment (CE) scheme, advanced age, number of children, relatively low education, literacy/numeracy problems, location in urban areas, lack of personal transport, low rates of recent labour market engagement, spousal earnings and geographic location. The results from the female model are broadly similar to those of males with successful labour market exit rising with third-level education, recent employment, a willingness to move for a job and good health, while the probability of remaining on the Live Register increases with number of children, literacy/numeracy difficulties, a history of unemployment and casual employment status. However, some gender differences are apparent. In particular, females who are married or separated are less likely to leave the Live Register, as are those whose spouse is a high earner. The magnitude of the impact of children on labour market entry is also higher for females. Regarding location, unlike males, females appear to derive no disadvantage from living in an urban location.

- Economic conditions have changed radically since the data used in this study were collected. However, this is unlikely to undermine the accuracy and predictive power of the profiling model as the principal factors that determine long-term unemployment risk – i.e., low levels of education, history of long-term unemployment, literacy/numeracy problems, etc. – do not vary with business cycle conditions. Furthermore, the dramatic increase in unemployment has generated enormous pressure on the capacity of all components of the public employment service, particularly the DSFA and FÁS. A profiling system, if implemented, would allow the rank ordering of those claiming Jobseekers Benefits and Allowance in terms of their relative risk of entry to long-term unemployment. This would then provide policymakers with a fair and rigorous basis on which to ration interventions and target them on those most at risk of long-term unemployment.

1. INTRODUCTION

Most people who become unemployed find another job within a few months. However, a substantial minority 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 job search or retraining. Profiling represents an attempt to overcome the dilemma between intervening early to assist those jobseekers who will need assistance to find another job, but wasting 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. Consequently, over the last decade or so many countries (e.g. Australia, the United States, Denmark and Germany) have developed profiling systems to both identify those with a high probability of becoming long-term unemployed and refer them to appropriate labour market programmes.

Statistical profiling is one specific type of profiling procedure that has been adopted by a growing number of public employment services around the world to identify and target their scarce re-employment resources at those jobseekers in greatest need. It is a tool whereby a numerical probability score, calculated on the basis of multivariate regression, determines the referral of an unemployed person to further employment services. Specifically, the score derived ranks each individual in terms of his/her risk of becoming long-term unemployed and public employment service (PES) staff can then use this score to identify those who are most in need of their assistance to help prevent them becoming long-term unemployed. Overall, the main objective in using statistical profiling is to deliver intensive services early rather than after long-term unemployment has already occurred. It is important to note at this point that a profiling system can only be successful in preventing those identified as being at risk of becoming long-term unemployed from falling into this trap if it is combined with delivery of targeted training and employment programmes that are known to be effective in enhancing the employment prospects of their participants.

In this report we develop a profiling model using administrative data, combined with survey data from a unique questionnaire that was administered to all persons in the Republic of Ireland who made an unemployment claim over a thirteen week period between September and December 2006. The study was initiated by the Irish Department of Social and Family Affairs (DSFA), which administered the specially designed questionnaire to all claimants for unemployment related payments – Jobseeker's Benefit and Jobseeker's Allowance – and which tracked the subsequent status of profiled claimants over a fifteen month period. The central objective in developing this profiling model is to provide policymakers, specifically the Irish DSFA, with a framework that will enable them to estimate an individual's likelihood of remaining on the Live Register after twelve months. The DSFA can then use the measure that is produced by the profiling model to both identify jobseekers that require immediate re-employment services and refer them for programmes designed to enhance their chances of securing employment. The identified individuals are referred to FÁS, the national employment and training agency. This type of intervention system would be in stark contrast to that currently operated under the National Employment Action Plan (NEAP) whereby all individuals are referred by the DSFA to FÁS for assistance after a three-month unemployment spell.[1] The analysis builds on previous research to develop a profiling model based on Irish survey data that was originally collected by the DSFA (Layte and O'Connell, 2005).

The existing blanket approach to assisting unemployed individuals to re-enter the labour market is potentially inefficient on a number of fronts. First, under the current three-month rule, many individuals who would have found employment on their own before a six, twelve or fifteen month point will receive support. Such interventions will ultimately prove unnecessary, thereby representing a waste of resources. Second, early interventions are preferable from the perspective of both cost and policy effectiveness, which suggests that the current three-month delay associated with policy activation is unlikely to be optimal.

There are a number of alternatives to the current largely indiscriminate intervention approach, which include eligibility rules, caseworker discretion, screening and profiling (Hasluck, 2008). While this report focuses on statistical profiling as an intervention approach, the following gives a brief description of some alternative strategies[2] that are also available, and which are used in some countries, either on their own or in combination with statistical profiling.

– *Eligibility rules* describes a process whereby individuals are channelled towards various forms of re-employment support on the basis of meeting certain criteria. The advantage of this system is that the development of clear-cut criteria rules makes it relatively cheap and straightforward to implement. However, the eligibility rules approach is still somewhat indiscriminate in that the needs of individuals falling into what will be relatively broad criteria-based categories are likely to remain diverse.

– *Caseworker discretion*, as the name suggests, describes a process whereby the PES interviewer uses his/her own judgement to direct the claimant towards the type of intervention that he/she feels is most appropriate to meet the jobseeker's needs. While such a process may be more responsive to individual needs

[1] The NEAP commenced in September 1998.
[2] Some countries (for example, Canada, Switzerland and Germany) have experimented with and/or implemented statistical targeting systems, which is an instrument that seeks to identify the most appropriate re-employment programmes for customers as opposed to just separating out those customers at risk of becoming long-term unemployed (see Colpitts, 2002; Frölich *et al.*, 2003; Gerfin and Lechner, 2002; Gerfin *et al.*, 2005; Lechner and Smith, 2007; Arnkil *et al.*, 2008; and Behncke *et al.*, 2006).

relative to the eligibility rules approach, it is still highly subjective, more expensive to implement and difficult to evaluate.

– *Screening* describes the process whereby the caseworker attempts to score the individual claimant's employability using typically psychological-based techniques, and, on the basis of a resulting ordinal employability score the claimant is directed towards the intervention that is designed to meet his/her particular score. The principal criticism of this approach relates to a lack of consensus regarding the most effective methods of screening. Furthermore, the approach again relies on a level of caseworker discretion and, therefore, cannot be considered wholly objective.

– *Statistical profiling* describes a method of assessment whereby the claimant's suitability for re-employment support is based on a probability measure generated by a formal statistical model. As a consequence of its fundamentally objective nature it is potentially a superior method of assessment compared to the approaches already discussed. There are, however, some potential drawbacks to the system which include the following: (a) the possibility that poorly performing models, which could arise if poor data are used or inappropriate variables were included in the model specification, may incorrectly identify individuals for intervention (i.e., deadweight[3]); (b) any statistical model that is developed will relate to a particular point in a country's business cycle and, as such, the model will require some updating as economic conditions change; and (c) the initial set up costs may be quite substantial. These issues are discussed further in Chapter 2, which provides a review of the international evidence on profiling systems.

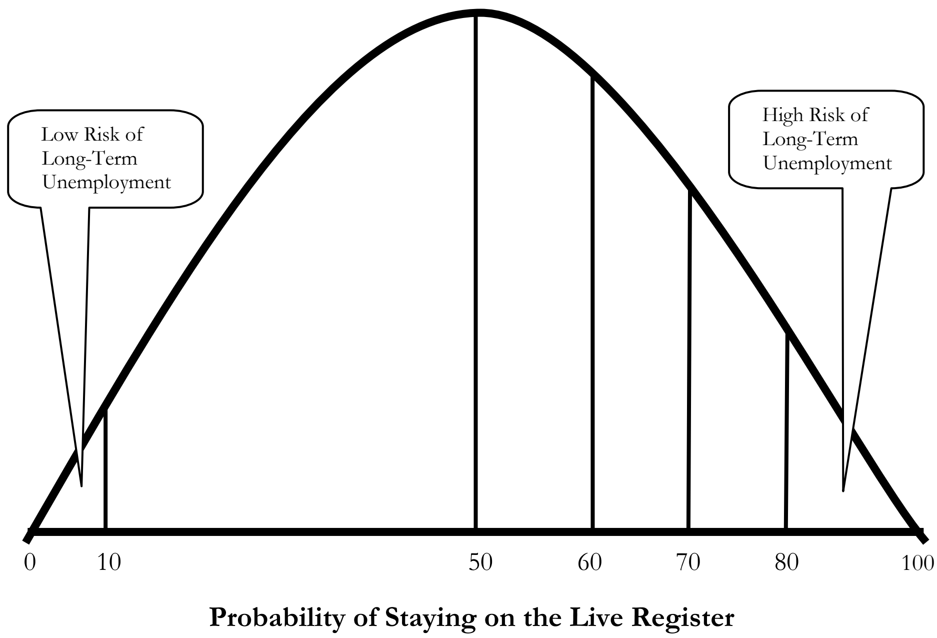
Despite some potential challenges, successful statistical profiling should present a more efficient and effective system given that the number of interventions will be lower and, provided such interventions are successful, the incidence of long-term unemployment will be reduced. Consequently, the burden on the Government Exchequer will be lower. Second, with a profiling system the intensity of interventions can be varied according to the risk of long-term unemployment. Third, a profiling score provides the caseworker with more detailed information on the challenges facing each individual claimant, which also allows for a more tailored approach to support individuals.

The general concept of statistical profiling is illustrated by the "Long-term Unemployment Risk Barometer" depicted in Figure 1.1.[4] Depending on his/her particular circumstances, each individual making an unemployment claim will have a risk of becoming long-term unemployed

[3] This describes the situation whereby an individual is identified, through any type of intervention mechanism, as being at risk of becoming long-term unemployed but is not at risk and is subsequently sent for re-employment assistance.
[4] The graph is for illustrative purposes only and does not reflect a belief that the risk of becoming long-term unemployed follows a normal distribution.

ranging from 1 to 100 per cent. Under the current NEAP, as each individual's risk of long-term unemployment is unknown, clients are referred to FÁS after they have been in receipt of an unemployment payment for approximately twelve weeks. Clearly this can give rise to substantial deadweight and, thus, is inefficient, as many of the referred individuals will be low risk and are, therefore, not in need of re-employment assistance. By providing the DSFA with an estimate of each individual's long-term unemployment risk, statistical profiling ensures that resources will be targeted only towards higher risk individuals. Furthermore, unlike the current system, referrals for those most at risk can take place immediately as opposed to waiting three months or more. Finally, profiling gives policymakers a flexible approach to intervention as the unemployment risk cut-off point for intervention can be altered depending on the Department's or Public Employment Service's objectives and/or resources.

Figure 1.1: Profiling "Long-Term Unemployment Risk Barometer"



Following the outline of this study's objectives, the remainder of the report is structured as follows. In Chapter 2, we provide an overview of other countries' experiences with profiling, empirical evidence on how effective their systems are and lessons to be learnt. Data and methodological issues are discussed in Chapter 3. A descriptive examination of the data is undertaken in Chapter 4, while the results from our statistical profiling model, conducted through regression analysis, are presented and discussed in Chapter 5. Finally, Chapter 6 provides a summary and conclusion along with some broad policy discussion.

2. Statistical Profiling in Practice: International Experiences

2.1 Introduction

During the 1990s, a number of countries experimented with statistical profiling models and two of them – the United States and Australia – introduced fully operational systems. Denmark followed suit in 2004 and Germany in 2005. A number of other countries have also experimented with some form of profiling as a means of targeting their employment services, specifically, the Netherlands, New Zealand and South Korea. Countries that are currently testing profiling models include Bulgaria, France, Hungary, Mexico, Slovakia and Sweden, (Hasluck, 2008; Arnkil *et al.*, 2008; De Koning and Van Dijk, 2004). Finland has just finished piloting a profiling system and is about to implement it (Behncke *et al.*, 2007).

The United Kingdom also experimented with a profiling model, however, the Department of Work and Pensions and JobCentre Plus[5] decided not to implement its system as a practical instrument following concerns around the model's accuracy (Gibbins, 1997; Wells, 1998).[6] However, a recent study by Bryson & Kasparova (2003) concluded that it would be beneficial to use profiling to predict the benefit spells of Jobseeker's Allowance (JA) claimants, lone parent and disabled individuals on benefit. Bryson and Kasparova (2003) argue that profiling represents a more accurate system of identification compared to random allocation. The results from this work have led the UK PES to implement a profiling system for jobseekers on incapacity benefit (Behncke *et al.*, 2007). According to Bimrose *et al.* (2007), one of the reasons why statistical profiling is still underdeveloped for other types of jobseekers in the UK is because of the limited administrative data; such data restrictions diminish the accuracy of any statistical profiling model.

[5] UK PES.

[6] See also Hasluck (2008).

2.2 Worker Profiling in the United States

Since 1993, when two sets of amendments[7] relating to unemployment assistance were passed by Congress, each US state has been required by law to develop and implement its own Worker Profiling and Re-employment Services (WPRS) system. WPRS consists of three basic steps: (i) early identification of unemployment insurance (UI) claimants most likely to exhaust their entitlement to benefits and, consequently, most at risk of becoming long-term unemployed; (ii) provision of re-employment services to these claimants; and (iii) collection of information on outcomes in order to check continuing benefit eligibility and to facilitate evaluations (OECD, 1998). Five prototype states were the first to implement the profiling law; these were Delaware, Kentucky, Florida, New Jersey and Oregon (OECD, 1999). As statistical profiling is technically complex, the US Department of Labour (USDOL) assisted states in their efforts to create their profiling systems[8] and by 1995 all states had operational WPRS systems in place.

In the WPRS system, data are collected on all persons starting a new spell of unemployment and these data are then used to predict each person's probability of exhausting his/her UI benefits.[9] This prediction, or score, comes from an econometric model, which is estimated using claimant data from the UI system along with aggregate data from external sources, such as the local unemployment rate. States vary in the number of covariates (i.e. explanatory variables) that they include in their model. For example, the profiling model for Washington state, which is one of the larger state models, includes 36 covariates, whereas the model for the state of Pennsylvania uses only eight (Black *et al.*, 2001). Due to civil rights issues, age, gender and race/ethnic group are factors that cannot be included in state models.[10] Consequently, the main variables used tend to be restricted to educational attainment, job tenure, previous occupation and previous industry.[11] Some states, however, include many additional covariates. Kentucky's profiling model, for example, contains 140 different explanatory variables, which includes factors such as past earnings, experience and UI participation.[12]

[7] These relate to: (i) the mandatory profiling of unemployment insurance (UI) claimants and (ii) compulsory participation of selected claimants in re-employment services.
[8] The USDOL provided states with a team skilled in econometrics and UI data systems to help them develop and refine their statistical models (Wandner, 1998).
[9] In order to keep deadweight to a minimum, a process is used to select UI claimants to profile. Specifically, only those who receive a cheque within the first five weeks of their claim and who pass a comprehensive screening mechanism are profiled. These individuals are then placed in a selection pool for re-employment services, which sorts them by their estimated probability. In some states, all new claimants who pass the characteristics screen and are profiled are placed in the selection pool, while in other states only those who are identified as "at risk" are placed in the pool. These latter states have placed a threshold value on the estimated probability that determines whether the profiled claimant ends up in the selection pool (OECD, 1999).
[10] Restrictions on the variables allowed in profiling models are also an issue in the EU, where in many countries "…it is forbidden to record so-called soft characteristics and attitudes in a database due to their stigmatising effect. Hence, alcohol abuse, etc., must be kept separately" (OECD 2002, p.230).
[11] It is argued that these variables may proxy, to some extent, for the omitted variables of age and gender (OECD, 1999).
[12] See Black *et al.* (2003) for the various variables that different states include in their profiling models.

In all states, profiled UI claimants are allocated to mandatory re-employment services according to their computed risk score; caseworker discretion is explicitly prohibited with these programmes (Frölich *et al.*, 2003; Bimrose *et al.*, 2007). However, caseworker discretion guides the assignment of other types of non-mandatory services (Lechner *et al.*, 2007).[13] Allocation also depends on the ability of local providers to supply re-employment services, which ultimately depends on their financial resources. Those jobseekers identified as being at risk of exhausting their UI benefit are required by law to participate in the re-employment programme provided, otherwise they risk losing their benefit.[14] Services provided vary considerably from state to state. A third of states offer only minimal re-employment programmes (five hours or less) but in about 45 per cent of states over half the profiled claimants are required to participate in additional services (Wandner and Messenger, 1999). For programme evaluation purposes, federal government regulations mandate that states collect data on the types of follow-up services provided and the number of participants in each.

2.3 Job Seeker Classification in Australia

Australia's experience with statistical profiling dates back to October 1994 when the Commonwealth Employment Service[15] introduced a two-stage profiling system – the Jobseeker Screening Instrument (JSI) and the Client Classification Level (CCL) - that allowed for the assessment of the risk of becoming long-term unemployed. Identified individuals were then given preferential access to case management and labour market programmes. In February 1998, after a major reform of employment services in Australia, this two-stage profiling system was replaced by the Job Seeker Classification Instrument (JSCI). The JSCI was developed by the Department of Employment, Workplace Relations and Small Business (DEWRSB)[16] and is operated by Centrelink, Australia's PES,[17] on behalf of the Department of Education, Employment and Workplace Relations (DEEWR). This new profiling system was established through a combination of formal research,[18] expert judgement[19] and wider

[13] Referral to training is not based on the UI claimant's profiling score, only referral to counselling, job search assistance and job placement is based on the computed risk score (Behncke *et al.*, 2006).

[14] In each state, however, there are circumstances whereby profiled job-seekers selected for re-employment services may be exempted from participation (OECD, 1999).

[15] Replaced by Centrelink (Australia's PES) in 1998.

[16] Originally the Department of Employment, Education, Training and Youth Affairs (DEETYA).

[17] Centrelink is a statutory authority responsible for delivering human services, such as employment assistance, on behalf of agencies of the Commonwealth Government of Australia (e.g. the DEEWR).

[18] An extensive survey of jobseekers was undertaken by the DEWRSB, called the 1997 JSCI Survey. This survey along with administrative data, dating back to 1995, was then analysed to identify the risk factors associated with prolonged unemployment. The factors that were tested in this survey have formed the basis of the JSCI statistical model.

[19] A Classification Working Group was established to make recommendations on additional factors which could not be tested in the 1997 survey but which also contribute to labour market disadvantage, factors such as homelessness and disclosed ex-offender status. This resulted in five additional (non-survey) factors being included in the JSCI statistical model.

consultations with major stakeholders and the employment services industry (DEWRSB, 1998; OECD, 2001).[20]

A new version of the JSCI was introduced in 2003 to reflect the changes introduced into Australian employment services under the Active Participation Model (APM).[21] Since this time, the JSCI has been used primarily for the identification at registration of those with the greatest risk of long-term unemployment. These jobseekers are then immediately eligible for assistance targeted to their individual needs.[22]

The statistical model that underlies the JSCI, which is a linear logistic regression model, estimates the relative weight or 'points' of 14[23] risk factors that were identified by the DEWRSB as being associated with long-term unemployment. This includes a jobseeker's age and gender, educational attainment, language and literacy, vocational qualifications, recency of work experience, stability of residence, indigenous/Australian born South Sea Islander status, country of birth, geographic location, disability/medical condition, family status/living arrangements, disclosed ex-offender, contactability and personal characteristics (e.g. poor motivation, poor presentation, etc.) requiring some judgement to be made by the caseworker. The weights (points) that the statistical model produces represent the independent effects of each risk factor on the predicted probability of a jobseeker becoming long-term unemployed, after controlling for the influence of all other factors included in the model.

Between 2003 and 2006, labour market conditions improved in Australia. This resulted in the statistical model that underlies the JSCI being re-estimated in 2006 to better capture jobseeker disadvantage.[24] Administrative data collected from the period September 2003 to August 2005 was used to re-estimate the logistic model. In the re-estimation it was found that the 14 existing risk factors associated with long-term unemployment continued to be significant. However, since the last version of the JSCI was implemented in 2003 the relative importance of the different risk factors, and therefore the JSCI weights (points) for these factors, had changed. Consequently, in July 2006, a re-estimated JSCI came in to operation. In addition to the reweighting of the 14 existing risk factors, a fifteenth factor to capture the additional disadvantage for

[20] See DEWRSB (1998) for the principals that guided the development of the JSCI.

[21] The APM incorporates a more active engagement of jobseekers through Job Network, a national network of private and community organisations dedicated to finding jobs for unemployed people, particularly the long-term unemployed, and other complementary employment and training programmes.

[22] Employment assistance is provided by Job Services Australia (JSA). JSA is a new approach to employment services that was introduced by the Australian Government on 1 July 2009. JSA replaces previous employment services such as Job Network (DEEWR, 2009).

[23] The original statistical model developed in 1998 consisted of 18 factors, five of which were non-survey identified factors. The changes made to JSCI in 2003, under the APM, saw the number of factors reduced to 14. Duration of unemployment, transport, proximity to labour markets (non-survey factor) and small community dynamics were the four factors that were omitted. Re-weighting of the remaining 14 factors was also conducted (see Lipp, 2005).

[24] The 2006 re-estimated JSCI takes account of the Welfare to Work changes that were announced in the 2005-06 Budget (see http://www.workplace.Programmes/JobNetwork).

Indigenous jobseekers in rural and remote communities was included in the revised statistical model.

A third review of the JSCI was conducted in 2008. This review resulted in the reweighting of the 15 factors included in the statistical model that underlies the JSCI,[25] and the addition of three new factors (proximity to a labour market, access to transport and income support history) to improve the JSCI's ability to assess disadvantaged jobseekers barriers to employment. This new version of the JSCI was implemented on 1 July 2009 (DEEWR, 2009).

To determine a jobseeker's JSCI score, information is collected by Centrelink staff[26] at the time of registration on the risk factors identified as having a significant impact on a jobseeker's probability of becoming long-term unemployed.[27] Points (i.e. weights) are assigned to each questionnaire response, along with the information that is used from administrative data on the jobseeker, and a total JSCI score is derived by adding the points (weights) for each of the long-term unemployment risk factors: the higher the score, the higher the probability of a jobseeker becoming long-term unemployed. Newly registered jobseekers with a very high probability of becoming long-term unemployed are classified as highly disadvantaged and are immediately sent for a Job Capacity Assessment (JCA).[28] All other eligible jobseekers are referred to the most appropriate form of support that will meet their individual needs.

2.4 The Danish Job Barometer

As of 1 December 2004, a profiling system has become an integrated part of the Danish national labour market policy. It was introduced under reforms to the provision of employment services in Denmark, which were undertaken in 2002.[29]

The system consists of several components, the first of which is a statistical model that is used as an initial screening device for identifying potentially long-term unemployed workers. The model employed is a duration model for the time spent in unemployment. Specifically, the model estimates a probability that an individual with certain characteristics will still be unemployed in six months time (i.e. 26 weeks)[30] conditional on the elapsed duration of unemployment, which at the date the unemployed

[25] Administrative data for the stock of income-support receiving jobseekers on 1 July 2007 was used to re-estimate the logistic model.

[26] In some circumstances, JSA staff or Job Capacity Assessors (JCA) can conduct the JSCI on behalf of the DEEWR.

[27] In the administration of the JSCI, all organisations are bound by the *Privacy Act 1998* when handling jobseekers' information.

[28] A JCA is a comprehensive assessment of a jobseeker's vocational and non-vocational barriers to employment and the impact these barriers have on the jobseeker's capacity to undertake work (DEEWR, 2009).

[29] The primary objective of the reforms introduced is to reduce the emerging public finance problem triggered by an ageing population by increasing their labour force by approximately 90,000 individuals by 2010.

[30] According to Rosholm et al. (2006), as the Danish model is further developed (e.g. inclusion of additional variables to capture educational attainment, etc.), it is planned to extend it so that it can make predictions for persons with an elapsed unemployment duration longer than 26 weeks.

person meets a PES caseworker can be anything from 4 to 30 weeks.[31] Consequently, the unemployed population used in the estimation of the duration model consists of those that have survived at least four weeks of unemployment.[32] In addition, all unemployment spells longer than 56 weeks are censored at this duration i.e. excluded from the model.[33]

The data used in the estimation of the Danish statistical model comes from an administrative register database called the Danish Register for Evaluation of Marginalisation (DREAM)[34] and consists of the entire inflow into unemployment during the period January 1999 to June 2003. DREAM is an event history file that includes weekly information on each individual's receipt of public transfer incomes, unemployment registrations and participation in active labour market programmes. The explanatory variables included in their model are a jobseeker's age, municipality of residence, marital status, sickness (receiving sick pay), immigrant status (generation and origin), year unemployment spell began, local unemployment rate, UI-fund, paternity leave and holiday pay, active labour market policies and labour market history. Measures such as educational attainment, previous wage and working experience are not in the dataset used. However, the Danish labour market authority is planning to increase this type of information in the register so that it can be used in their statistical profiling model.

The model is estimated using 120 subgroups, stratified according to age (2), gender, benefit eligibility (2) and region of residence (15). According to Rosholm *et al.* (2006), the effects of some of the explanatory variables vary across the different subgroups but some consistent patterns do emerge. Specifically, age, marital status, immigrant status, year unemployment spell began and local unemployment rate were all found to have a significant impact on unemployment duration, as was holiday and paternity leave, sickness and labour market history.

The predictions of becoming long-term unemployed that come from the statistical profiling model are presented in a graphical format to PES staff in what is known as the *Job Barometer*. The predictions are divided into three categories: (i) high risk of long-term unemployment, (ii) medium risk of long-term unemployment and (iii) low risk of long-term unemployment. Which area is high-lighted on the *Job Barometer* for an unemployed individual depends on the way his/her probability deviates from a population mean. This information is then used by caseworkers to assess the jobseeker's employability. The next stage after this in the Danish profiling system is an analysis by a caseworker of the unemployed

[31] The first interview conducted by the PES with a jobseeker depends on the type of benefit he/she is receiving, of which there are two in Denmark: (i) Unemployment Insurance (UI) and (ii) Social Assistance (SA) – see Rosholm *et al.* (2006) for more details on Denmark's two-tired system for unemployed workers. Jobseekers on UI do not meet a PES caseworker during the first four weeks of unemployment, while those receiving SA could meet a PES staff member on the first day of their unemployment.
[32] Separate models are estimated for the two types of jobseekers that exist in Denmark, UI and SA claimants, and this restriction only applies to the UI model.
[33] This 56 week censoring restriction only applies in the UI model. In the SA model the restriction is 52 weeks. The restrictions differ because of time differences in when each type of unemployed worker is first interviewed by a PES staff member.
[34] Complied by the Danish Labour Market Authority (DLMA).

individual's public assistance record.[35] After this, there is a dialogue guide for the caseworker's communications with clients designed to identify strengths and weaknesses in relation to the labour market.

Overall, a Danish caseworker's assessment of how to treat an unemployed person is partially based on the prediction that the statistical model gives rise to, with the remainder based on his/her own subjective assessment of the individual.

2.5 The German Profiling System

Having faced high unemployment rates for more than a decade, in addition to having one of the highest long-term unemployment rates in Europe, the German government implemented a comprehensive set of labour market reforms during the period 2003 to 2005.[36] The main focus of these reforms was to reduce long-term unemployment through significantly faster integration of jobseekers into work. This led to changes in the organisational structure of the German PES, the Bundesagentur für Arbeit (BA), at the beginning of 2004. A core element of the BA reform process was the introduction of statistical profiling of jobseekers, which took place in 2005. In addition to identifying the long-term unemployed, profiling in the German PES also serves as a tool for separating customers into different categories, the determination of individual assistance and also as an instrument for the allocation of resources (Arnkil *et al.*, 2008).

The statistical component of the profiling model, which is based on a binary probit model, incorporates personal characteristics and labour market information. The model computes a single risk factor for each jobseeker that measures his/her probability of becoming long-term unemployed (Bimrose *et al.*, 2007). Based on their computed risk factor, jobseekers are classified into one of the following four categories: (1) *market clients*, which are individuals who are viewed as being job ready and have the highest probability of finding employment; (2) *clients for counselling and activation*, which are jobseekers that mainly need to be activated in their job search or that need minor adjustments to their skills through short training; (3) *clients for counselling and qualification*, which are individuals that need more attention and are likely to be assigned to training programmes and other measures that will increase their mobility or flexibility; or (4) *intensive assistance clients* who are jobseekers that require special attention as they face the lowest chances of re-employment and are at risk of becoming long-term unemployed.[37] Based on the individual profiling result, tailor-made action programmes (*Handlungsprogramme*) for each client group are developed, of which there are six.[38]

In order to improve the allocation process of jobseekers to appropriate re-employment programmes, BA (the German PES) introduced a statistical targeting system in 2005 called the *Treatment Effect and Prediction* (TrEffeR)

[35] This information is also used in the statistical profiling model.
[36] Known as the *Hartz* Reforms (see Arnkil *et al.*, 2008).
[37] An analysis of the inflow of jobseekers between January and March 2006 showed that 23 per cent were categorised as *market clients*, 20 per cent as *clients for counselling and activation*, 16 per cent as *clients for counselling and qualification* and 30 per cent as *intensive assistance clients*. In the remaining 11 per cent of cases, no clear assignment to one of the four categories was possible (Arnkil *et al.*, 2008).
[38] See Arnkil *et al.* (2008) for more details on these programmes.

system. The idea behind statistical targeting systems is that a particular re-employment programme impacts differently on diverse subgroups of the unemployed at different stages in their unemployment spell.[39] Thus, TrEffeR creates a computer tool for caseworkers designed to assist in choosing the optimal strategy for each unemployed person. This targeting system also generates systematic and semi-annual information about the effectiveness of all available labour market instruments for each of the regional labour agencies in Germany (Arnkil *et al.*, 2008).

2.6 Profiling Models in Other Countries

A number of other countries have experimented with some form of profiling, though not necessarily based on a statistical model, as a means of targeting their employment services but none have implemented systems on the same scale as the United States, Australia, Denmark or Germany.

The Netherlands

In 1999 the PES in the Netherlands, known as the Centre for Work and Income (CWI), introduced the *Kansmeter* (the chance meter), which is a profiling tool used to identify a jobseeker's distance from the labour market: this distance is measured by the probability of the jobseeker finding a job within a year (Weinert, 2001). The *Kansmeter* is based on a questionnaire, which the caseworker conducts with the jobseeker at his/her initial registration interview. Information regarding the jobseeker's personal situation, occupational and skill profiles and his/her capacity for independent job search is gathered through this questionnaire. A score, not derived from a statistical model, is allocated to each response, which the caseworker adds up to derive a measure of the jobseeker's probability of finding a job within a year.[40] The score derived classifies the jobseeker into one of four phases reflecting employability, where 1 represents the lowest risk and 4 the highest.[41]

There was considerable dissatisfaction in the Netherlands with this profiling model, specifically in relation to its predictive power: in only 3 out of 5 cases was the *Kansmeter* accurately predicting the timing of exit from unemployment. Following this, subsequent re-employment service organisations did not use the profiling results (Tergeist and Grubb, 2006). This led the Ministry of Social Affairs and Employment to replace the *Kansmeter* in 2006 with a new profiling tool called the *ABRoutering*, which classifies jobseekers into two groups based on their capacity for independent job search (Tergeist and Grubb, 2006). This two group classification is based on a job-seeker's probability of finding a job within 6 months, which appears to be derived using the same scoring system[42] that was used with the *Kansmeter* (OECD, 2008).

[39] See footnote 2 (Chapter 1).

[40] An econometric model is not used. Instead, instructions are given to caseworkers on how to calculate a score (OECD, 2002). De Koning *et al.* (2000) describe estimated econometric models used to calculate profiling scores in the Netherlands prior to the introduction of the non-statistical *Kansmeter* profiling instrument. Region, education, ethnic origin and age emerged from these models as the most important factors determining the probability that a person becomes long-term unemployed.

[41] For more details on the post-profiling interventions see OECD (2002), Weinert (2001) and Tergeist and Grubb (2006).

[42] Not a statistical profiling model.

In summary, while the Dutch system can be considered as a profiling system in the strictest sense, it differs from those applied in other countries due to the fact that the weights applied to the various risk factors are based on a subjective assessment as opposed to a formal statistical model.

New Zealand

In response to the growth in long-term unemployment that took place in New Zealand during the 1990s, some economists began examining statistical profiling using the administrative database maintained by New Zealand's PES, the New Zealand Employment Service (NZES)[43] (Gardiner, 1995; Watson *et al.*, 1997; Obben *et al.*, 2001; Obben *et al.*, 2002; Obben, 2002). However, to date, no formal statistical profiling model has been implemented. Instead, New Zealand PES caseworkers use a scoring system that is based only partially on a statistical model to classify jobseekers according to their employability (OECD, 2002). All items in the scoring system were selected according to "their capacity to predict unemployment and their usefulness in client management as determined by staff consultation, regression analysis and the review of literature" (OECD, 2002, p. 237). Caseworkers can overwrite the score produced by the scoring system; however, they have to provide a reason for doing so.

A potential explanation for the lack of a formal statistical profiling model in New Zealand may lie in the fact that successive studies (Gardiner, 1995; Watson *et al.*, 1997; Obben *et al.*, 2001; Obben *et al.*, 2002; Obben, 2002) have found that the administrative data is not sufficient to generate an accurate profiling model.

South Korea

A profiling instrument based on the probability of becoming long-term unemployed has been in use in South Korea since July 2000. Age, education, health, gender, relation with household head, marital status, work experience and local labour market conditions are the variables that they include in their model. However, importantly, the system is voluntary for the unemployed and it is only used as an advisory tool by caseworkers in selecting the most appropriate re-employment intervention for their client (OECD, 2002).

2.7 Evidence on Effectiveness of Statistical Profiling

There are several issues that must be addressed when evaluating how effective a profiling system is. First of all, the goals of the PES must be taken into consideration (Black *et al.*, 2001). If the objective of the PES is to serve those jobseekers most in need i.e. equity goal, as opposed to serving those with the largest net benefits from participation i.e. efficiency goal, then the basis of assessment will be different. Secondly, it is important to demonstrate, if possible, that any other system that is used to identify those most at risk of becoming long-term unemployed, such as eligibility criteria or caseworker discretion, is less effective (Hasluck, 2008). Some research has been undertaken on the effectiveness of statistical profiling by those countries that have implemented fully operational systems, a summary of which is provided next.

[43] In 1997, the PES in New Zealand became known as Work and Income. Since 2001, this service has been under the remit of the Ministry of Social Development (prior to this, the Department of Labour had responsibility for New Zealand's PES).

United States

In relation to the WPRS profiling system in the United States, evaluations of it indicate that in states where adequate statistical models have been developed, the system works well in terms of identifying those in greatest need of re-employment services (Hasluck, 2008). However, Black *et al.* (2001), find that many existing state profiling models have poor predictive power due to a lack of covariates as opposed to the form of dependent variable or estimation procedure used.[44] Their research indicates that state models that contain a rich set of covariates, such as the Kentucky state model, have superior predictive performance over those that only include a limited number of explanatory variables. This view that the predictive power of state profiling models can be improved by controlling for a larger number of covariates was reiterated by Black *et al.* in 2003. It was also a recommendation that was made by a WPRS policy group that was established in 1998. This group also advised that, due to changing economic conditions, states should update and refine their model every two to three years in order to maximise the model's accuracy (Wandner & Messenger, 1999). Thus, the research that has been undertaken to-date on the effectiveness of the WPRS statistical profiling tool concludes that the system does a good job on accurately identifying those who are most in need. Wandner (1998) also found that statistical profiling was superior to staff judgement using screening at identifying those at risk of becoming long-term unemployed.[45]

Australia

In Australia, the DEEWR has regularly commissioned independent consultants to undertake evaluations of the JSCI's effectiveness and efficiency. Such assessments have resulted in the JSCI being updated on three occasions, in 2003, 2006 and again in 2009. According to Lipp (2005), the 2003 and 2006 updates increased the accuracy of the JSCI, specifically in terms of its predictive power. Longitudinal analysis of JSCI by Centrelink found that the JSCI had identified the appropriate level of service in 90 per cent of cases.[46] Lipp (2005) has concluded that the JSCI has been effective in sorting jobseekers, in terms of their employability, and this has, consequently, reduced deadweight. However, as Hasluck (2008) points out, the gain of profiling over other forms of assessment has yet to be established within an Australian context.

Denmark

In relation to Denmark, Rosholm *et al.* (2006) carried out an assessment on the model's predictive performance and found that overall the fraction of correction predictions produced by the model is 66 per cent. Rosholm *et al.*

[44] According to the OECD (1999; 2002), the forecasting accuracy of profiling models can be improved by including an individual's unemployment history prior to his/her current unemployment spell as an explanatory variable, along with information on access to transport facilities and, if possible, variables that capture a jobseeker's motivation to find work (e.g. willing to move for a job). Le & Miller (2001) argue that it is the individual's most recent labour market history that is relevant, thus, gains in forecasting accuracy can be obtained by using individual history data relating to just the last few years.

[45] See also OECD (1999).

[46] It is not possible to assess yet the impact that the most recent changes to the JSCI, those implemented in July 2009, have had on the JSCI's predictive power.

(2006) attribute the success of the Danish model to its large number of covariates.

Germany

With respect to Germany, the effects on faster reintegration of the customer segmentation model and the action programmes for each client group are still under evaluation. However, on a macro-level a recent study shows an increase in matching efficiency due to the reforms of the PES that were introduced (Fahr and Sunde, 2006).

In summary, while the evidence has demonstrated that it is possible to generate accurate models from a statistical standpoint, the superiority of profiling over other strategies needs further research. Nevertheless, despite the lack of direct evidence, the fact that two of the worlds most significant economies – the USA and Australia – have consistently persisted with profiling provides some support for its relative superiority.

2.8 What Can We Learn?

This review of other countries' experiences with statistical profiling highlights a number of key points that should be borne in mind when designing and implementing such a system. These are briefly set out below:

– In order to minimise deadweight, selection criteria should be used to identify those who should be profiled in the first place, as is the case in the United States.[47] For example, only those who receive a social welfare payment should be profiled by the DSFA as opposed to everyone who enters a social welfare office to make a claim. In addition, a screening test should be applied to claimants to eliminate those who may be only receiving a payment for a short period of time, individuals such as college students, seasonal workers, etc.

– For those countries not depending solely on administrative data, the accuracy of any profiling model depends crucially on the choice of variables. For example, when the Australian model was updated they concluded that some variables, such as duration of unemployment and small community dynamics, were largely irrelevant. In America, on the other hand, authorities have included new variables (e.g. occupation) since their original model was developed. Clearly, the importance of variables will differ from country to country and over time as economic conditions change. This suggests that profiling, far from being a once-off operation, requires continuous assessment and updating to ensure accuracy levels are maintained and improved.

– The integrity and accuracy of the data collection process is crucial to the success of any profiling system. It is essential, therefore, that PES staff have appropriate skills to both ensure that jobseekers give correct and full information and that the information is inputted correctly into the profiling model (Lipp,

[47] See footnote 9.

2005; Bimrose *et al.*, 2007). It is also important that PES IT staff have the necessary skills required to implement and maintain a profiling system (Black *et al.*, 2001).

3. DATA AND METHODOLOGY

3.1 Data Sources

The data collection process for this study was quite unique. A specially devised questionnaire was administered to all individuals registering an unemployment claim during a 13 week period, running from September to December 2006. Individual claimants were then tracked for a further 78 weeks, allowing us to develop six, twelve and fifteen month profiling models. Specifically, we use weekly information from the DSFA's Integrated Short-Term Scheme (ISTS) i.e. the Live Register database to establish if the person was still claiming benefit at the end of each observation period respectively.

Regarding the information used in our profiling model, the Live Register database contains some information on individual characteristics that are useful for statistical profiling. For instance, the administrative dataset holds relatively detailed information on marital status, spousal earnings and location.[48] Nevertheless, the bulk of the information on the background characteristics required to develop a profiling model was gathered through the specially devised questionnaire. This survey collected data on factors such as educational attainment, literacy/numeracy levels, health, access to transport, employment/unemployment/job history, and participation on PES provided job schemes, such as the Community Employment (CE) scheme.[49]

From here on in the report, we focus on the twelve month profiling model. However, information on the six and fifteen month models are provided in Appendices A to D, with a brief discussion of the results produced by each of the three models presented in Chapter 5.

[48] Captures the social welfare office where the claimant signs on the Live Register.
[49] The CE scheme, which is operated by FÁS, is designed to help individuals who are long-term unemployed, and other disadvantaged individuals, to get back to work by offering part-time and temporary placements in jobs based within local communities.

3.2 Sample Information

The total number of records contained within the initial profiling database was 60,189 (Table 3.1). After the elimination of duplicates and individuals who had registered for social welfare benefits other than Jobseeker's Allowance (JA) or Jobseeker's Benefit (JB), the population fell to 57,162. The DSFA's specially devised questionnaire was successfully administered to 44,075 of this claimant sample. However, not everyone who made claims for JA or JB were successful and, given that we can only consider individuals who are actively in receipt of unemployment benefits,[50] we further exclude non-successful applicants, which gives a final sample of 33,754. A preliminary probit model indicated that those individuals most likely to be awarded an unemployment payment tended to be single, previously unemployed, proficient in English, older, have children and a relatively high earning spouse.[51]

When constructing the twelve month model, we consider the status of individuals at week 65 in the data.[52] Initially, leavers are defined as individuals who had their claim closed and, consequently, had left the Live Register at some point prior to 65 weeks and did not have a subsequent JA or JB unemployment application activated. On the basis of this initial categorisation, 59 per cent of the sample is designated as leavers, with 41 per cent classified as stayers. However, not all of this leaver sample, as it is currently defined, will have exited to the labour market, nor will all of the identified stayers have remained consistently on the Live Register for a period of 65 weeks. Given that the objective of profiling is to identify those at risk of becoming long-term unemployed, adjustments are required to our currently defined leaver and stayer samples to ensure that we correctly differentiate genuine labour market exit cases from those more likely to be welfare dependent. These sample adjustments are documented in Sections 3.5 and 3.6 below, which is where we provide more detailed information on the final leaver and stayer samples used to build our twelve month profiling model.[53]

Table 3.1: Sample Information

Profiling Data	Numbers
Original Population	60,189
Exclusions:	
– Duplicates	*1,164*
– None JA and JB Claims	*1,863*
	57,162
Questionnaire Information	44,075
JA and JB Claims:	33,754
– Leavers at 12 Months	*19,853 (59%)*
– Stayers at 12 Months	*13,901 (41%)*

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

[50] Selection criterion imposed to minimise potential deadweight.
[51] Results available from the authors on request.
[52] Given that the population for the study was constructed over a 13 week period, the 65 week cut-off point allows for the possibility that each individual could have remained on the Live Register for a period of 52 weeks. The cut-off points used for the six and fifteen month models were weeks 39 and 78 respectively, which means that claimants could have been signing on for a period of 26 and 65 weeks in each of these models respectively.
[53] See Appendix A for information on the six and fifteen month models.

3.3 Questionnaire Non-Respondents

The survey questionnaire was not successfully administered to all social welfare claimants.[54] Specifically, there are almost 11,000 individuals for whom no survey information was gathered. It is important to ensure that these individuals do not differ significantly, in terms of their characteristics, from the rest of the claimant population for whom information was gathered. Consequently, the DSFA and the ESRI undertook a series of checks to ensure that the final sample used to construct our profiling models had not been adversely affected by this sample attrition. Table 3.2 compares the respondent and non-respondent samples on some broad characteristics available in the Live Register database. In terms of gender and marital status, both the respondent and non-respondent samples are virtually identical. However, non-respondents were slightly younger and a higher proportion were also non-Irish, suggesting that this sub-group contained a larger number of individuals who are likely to have gone abroad (e.g. gap year individuals) or were returning non-Irish nationals. Nevertheless, the differences are relatively minor and we are confident that any results generated by our data, and therefore our profiling model, are fully representative of the total social welfare claimant population.

Table 3.2: Comparison of Questionnaire Respondents and Non-Respondents (Per Cent)

	Respondents (%)	Non-Respondents (%)
Characteristics:		
Male	57.5	58.1
Married	79.6	80.1
Age	39.9	35.7
Irish National	84.3	80.8

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS).

3.4 Methodology

As stated previously, the objective of profiling is to develop a system of identifying those individuals who are most at risk of becoming long-term unemployed so that policymakers can then target such individuals for early intervention. Consequently, the approach we adopt is not simply one whereby we model the likelihood that an individual's unemployment claim will close after twelve months,[55] given that a large number of such claim closures are likely to remain welfare dependent. For example, an individual's claim for JB[56] may close due to the fact that his/her national social insurance contributions, known in Ireland as Pay Related Social Insurance (PRSI), have exhausted and, as a consequence, he/she may have a subsequent claim activated for the less restrictive JA.[57] Therefore, claim closure may not necessarily equate to an exit from unemployment into the labour market. Similarly, an individual may well cease to be technically unemployed but remain welfare dependant; for example, his/her JB or JA claim may close because he/she has transferred to a lone parent or

[54] Out of 57,162 claimants, 44,075 completed the DSFA's profiling questionnaire.
[55] Or six or fifteen months.
[56] Access to JB is restricted to individuals with sufficient national social insurance contributions (i.e. PRSI); furthermore, access to JB payments is restricted to either a twelve month (minimum of 260 paid contributions) or nine month period (less than 260 paid contributions).
[57] Eligibility for JA does not require PRSI contributions.

disability benefit. At the same time, there are some individuals in our data who were claiming unemployment benefit at the end of our twelve month observation period who spent a substantial proportion of this time in the labour market. Such cases are not technically long-term unemployed, thus, they need to be reclassified accordingly. In the next two sections in this chapter, we set out the adjustments made to our initial leaver and stayer samples, as defined in Section 3.2 (see Table 3.1), which leads to the final samples used in our profiling models.[58]

3.5 Leavers' Sample Adjustments

Within this study, individuals whose JB or JA claims have closed but who remain on welfare are distinguished from those who have exited to the labour market. Specifically, for the purposes of our model, such individuals are grouped alongside those whose original JB or JA claims remained active throughout the observation period.[59] The rationale for this approach is that we want to pinpoint those individuals most likely to remain welfare dependent and ignore the more administrative aspects of the support system, as clearly it would be virtually impossible to account for such factors when profiling takes place, and these are not pertinent to the objective of the study. Nevertheless, it is worth pointing out that profiling may aid the administrative process in that any individual not in receipt of the most appropriate form of assistance, for example disability allowance, will be quickly identified under the profiling system as they are likely to have a high long-term unemployment risk and be sent for early intervention. However, to reiterate, the fundamental assumption underlying our modelling approach is that any individual who remains on welfare at the end of the observation period is treated as a "stayer" in the data, whereas those who have exited to the labour market for employment and have not re-entered the system is defined as a "leaver".

In addition, we focus on an individual's claim status at the end point of our observation period only i.e. at six, twelve or fifteen months. In adopting this approach, we ignore the possibility that an individual's original claim may have closed as a result of a successful exit to the labour market and that they subsequently re-entered the system and had another claim activated within six weeks.

While some obvious adjustments can be made using our data – for example, individuals whose claims were closed due to death or prison, etc., are excluded from our sample – it is less clear how to treat individuals whose reason for closure is more ambiguous. In particular, there are a significant group of individuals in our data whose reason for closure is unknown and, despite the fact that such individuals have not transferred to a related benefit, we do not have enough information to allow us to categorise such persons as either leavers or stayers. It is not sufficient to assume that such individuals are labour market active, as, particularly in the case of females, it is also possible that they may be both inactive and non-welfare dependant. Given this, we have chosen to exclude these unknown reasons for closure individuals. However, we do carry out some sensitivity tests around this grouping in our models.

[58] See Appendix A for information on the leaver and stayer samples used in the six and fifteen month profiling models.
[59] Six, twelve or fifteen months.

Thus, not all unemployment claim closures will be exits to the labour market as some will move into other forms of assistance and, therefore, remain welfare dependant. As a result, of the 19,853 leavers discussed in Section 3.2,[60] 15,115 are designated as labour market entrants[61] and 2,377[62] are reassigned as stayers, on the grounds that they remain welfare dependant. A further 2,361 leaver cases are eliminated from the sample[63] as their reason for closure is unknown.

Consequently, just over three-quarters of the 19,853 claims that closed over the twelve month observation period were designated as genuine leavers to the labour market (76 per cent), with a further 12 per cent dropped due to a lack of information on their reasons for closure. With respect to the remaining 2,377 (12 per cent) of leavers that were redefined as stayers, the bulk of such individuals had transferred to another benefit (disability or JA) or had their payments stopped temporarily for administrative purposes. Table 3.3 gives the specific reason for closure for those individuals whose claims had closed at the end of the twelve months, the information that was used to make the adjustments to the leaver sample.

Table 3.3: "Reason for Closure" Information for Leavers that Left the Live Register Before Twelve Months

	Number	Per Cent	Status[1]
Signed off and gone to work	11,409	57	C
Failed to sign on	3,369	17	C
Gone to general benefits (disability, sickness, etc.)	846	4	WD
Gone on FÁS course (may be EAP referral)	640	3	E
Customer exhausted JB entitlement (may have gone to JA)	579	3	WD
Unknown reason for signing off	492	2	E
Person failed to sign (note: some quickly reinstated)	355	2	WD
Claimant is gone abroad	337	2	C
Claimant returned to college	270	1	E
Claim disallowed – not available for work	251	1	E
Gone to CE scheme	248	1	E
Claimant should be on disability benefit	126	1	WD
Did not collect weekly payment (note: may be quickly reinstated)	107	1	WD
Claim is disallowed – insufficient contributions and/or not habitually resident	105	1	E
Gone to retirement pension	80	0	E
Gone to carers allowance or benefit	70	0	WD
Person failed to furnish requested documentation	67	0	WD
Gone on to old age pension	52	0	E
Transferred to disability allowance	49	0	WD
Claimant has reached the age of 66 (pension age)	37	0	E
Claim disallowed – means in excess of weekly rate payable	33	0	WD
Payment change – Still on the Live Register	28	0	WD

[60] See also Table 3.1.
[61] Our definition of labour market leavers not only includes those who had signed off and were gone to work but also those who had failed to sign on (3,401) and those that were gone abroad (373). See Table 4.1 for more details on the coding of closures in our twelve month model.
[62] This brings our stayers population to 16,278.
[63] The sample now becomes 31,393.

Table 3.3: "Reason for Closure" Information for Leavers that Left the Live Register Before Twelve Months (Continued)

	Number	Per Cent	Status[1]
Transferred to maternity allowance	26	0	E
Closed as person has become an adult dependant on spouse's claim	25	0	WD
Claimant is deceased	23	0	E
Gone to maternity	22	0	E
Claim disallowed – customer did not disclose full details of his/her means	20	0	E
Claimant held in custody	20	0	E
Closed - gone to other than Social Welfare pension	15	0	WD
Unknown – code 12	14	0	E
Claimant no longer at address stated (HSE)	14	0	WD
Disability benefit first and final cert received (1 cert only)	13	0	WD
Person going from JB to optional JA	12	0	WD
Unknown – code 13	11	0	E
Claim was withdrawn and lapsed	11	0	E
Gone to invalidity pension	10	0	E
Should not be in sample (DFSA)	10	0	E
Claimant's location unknown	9	0	E
Claim disallowed – not qualified for JB (insufficient contributions)	5	0	WD
JB transferring from abroad and paid manually	5	0	WD
Claimant has returned to work after maternity	4	0	E
Maternity – unfit for work	4	0	E
PT job – still on Live Register	3	0	WD
Payment suspended and claim closed	3	0	E
Other[2]	23	0	-
Total:	19,853	100	
Closed (C)			*15,115*
Eliminated (E)			*2,361*
Welfare Dependent (WD)			*2,377*

Note: [1] Status: C = Closed; E = Eliminated; WD = Welfare Dependent.
[2] For confidentiality reasons, we cannot disclose information when the number of cases is two or less.
Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS).

3.6 Stayers' Sample Adjustments

In addition to amending the initial leavers' sample, there is some uncertainty surrounding the stayers' population and some adjustments are necessary. In particular, there is a need to re-categorise as leavers individuals who had, for a limited spell, exited to the labour market. The rationale for this is straightforward in that our profiling model is designed to distinguish individuals likely to exit to the labour market from those who will remain long-term welfare dependent. In the first instance, we assign any twelve month stayer who had been active in the labour market in the six month model[64] as a leaver.[65] This modification brings our leaver and stayer samples to 16,515 and 14,878 respectively.[66] As stated previously, the

[64] Of the 10,814 individuals identified as leavers in the six month model, 9,042 remained off the Live Register at the 65 week time point.
[65] There are 1,790 such individuals.
[66] In this adjustment, we also reassigned 390 leavers as stayers on the grounds that they had an unemployment duration of 52 weeks or more before exiting to the labour market.

stayers' data will also contain individuals who exited the Register for a substantial period during the observation period. Here we define substantial as greater than six weeks – before re-entering the Live Register at a later period. There are 3,712 such individuals. In terms of allocating these individuals in the data, we apply the same rules as before with respect to the reason for closure preceding the prolonged absence from the Live Register. Based on their closure information, (i) 2,241 (60.3 per cent) re-entrants were deemed to be labour market exits, (ii) 631 (16.9 per cent) had an unknown reason for closure and were dropped from the sample, (iii) with the remaining 840 (22.7 per cent) moving to another form of benefit and, therefore, remaining as stayers. Thus, our final sample becomes 30,762, of whom 18,756 (61.0 per cent) are leavers and 12,006 (39.0 per cent) are stayers (see Table 3.4). It is important to re-iterate that not all stayers remain on the Live Register at 65 weeks. In fact, 2,614 are no longer classified as unemployed with the largest proportion of such individuals transferred to general benefits and, thus, are still welfare dependent.

Table 3.4: Twelve Month Model Leavers' and Stayers' Sample Adjustments

Profiling Data	**Numbers**
Original JA and JB Claims Sample:	*33,754*
– Leavers at 12 Months	19,853 (59%)
– Stayers at 12 Months	13,901 (41%)
Leavers' Sample Adjustments:	
1. Welfare Dependent Leavers Redefined as Stayers	2,377
2. Unknown Reason for Closure Cases Eliminated from Sample	2,361
3. Leavers with 52Plus Weeks of UE Duration Redefined as Stayers	390
Stayers' Sample Adjustments:	
1. Apparent Stayers Redefined as Leavers	4,031
2. Unknown Reason for Closure: Cases Eliminated from Sample	631
Final JA and JB Claims Sample:	*30,762*
– Final Leavers Sample at 12 Months	18,756 (61%)
– Final Stayers Sample at 12 Months	12,006 (39%)

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

4. Bivariate Analysis

4.1 Introduction

Given that the objective of our statistical profiling model is to differentiate individuals that leave the Live Register and enter the labour market from those who stay in the system, in this chapter of the report we examine some of the key characteristic differences that distinguish the two groups using a simple descriptive framework.[67]

4.2 Key Characteristic Differences Between Live Register Stayers and Leavers

Table 4.1 reports the average incidences of each group across some key characteristic areas, such as age, gender, marital status, number of children, perceived health, apprenticeship training and basic skills. With respect to age and gender, any differences between the stayers and leavers appear to be marginal; however, leavers are slightly younger and/or more likely to be male. In relation to marital status, individuals who are single appear more likely to exit the Live Register to the labour market relative to their married counterparts. It is probable that the marital status variable is proxying for the influence of factors related to higher levels of labour market mobility among single individuals and a lower reservation wage[68] due to the absence of dependant children. Within the profiling questionnaire, respondents were asked to subjectively rate their current health status and, as might perhaps be expected, leavers were found to be in somewhat better health, with 95 per cent reporting a health status of very good/good compared to 89 per cent of stayers.

The profiling questionnaire also collected information on the incidence of apprenticeship training and perceived levels of basic numeracy and literacy. While leavers were slightly more likely to have served an apprenticeship, 15 per cent compared to 13 per cent of stayers, much starker differences were apparent with respect to basic skills. The incidence of literacy and numeracy problems among stayers was twice that of leavers, suggesting that a lack of basic educational attainment could represent a substantial barrier to full labour market participation. Similarly, claimants who felt they had problems with basic English proficiency were also less likely to exit to employment, however, the gap between the two groups was less pronounced than for literacy/numeracy.

Finally, claimants who had access to their own transport were found to be substantially more likely to leave the Live Register, which again is likely to reflect their ability to search for employment over a greater geographical

[67] The descriptive analysis presented here is based on the twelve month model stayer and leaver samples.
[68] This is the lowest wage rate a person will be willing to accept to enter the labour market. The reservation wage will be related to the level of state benefits forgone on entering employment.

distance. However, access to public transport does not appear to represent a significant factor in determining the rate of exit from unemployment into the labour market.

Table 4.1: Key Characteristic Information on Stayers and Leavers (Per Cent)

	Stayers (%)	Leavers (%)
Age	37.7	35.7
Gender:		
Male	*57.2*	*57.9*
Female	*42.8*	*42.1*
Total:	100.0	100.0
Marital Status:		
Single	*49.1*	*57.3*
Cohabits	*4.8*	*4.1*
Married	*37.9*	*33.1*
Separated/Divorced	*7.3*	*4.7*
Widowed	*0.9*	*0.8*
Total:	100.0	100.0
Children	2.8	1.8
Perceived Health Status:		
Very Good Health	*48.6*	*60.8*
Good Health	*40.2*	*34.6*
Fair Health	*9.6*	*4.3*
Bad Health	*1.4*	*0.2*
Very Bad Health	*0.2*	*0.1*
Total:	100.0	100.0
Apprenticeship	12.6	14.9
Literacy/Numeracy Problems	9.7	4.6
English Proficiency	3.3	2.5
Own Transport	55.6	63.2
Public Transport	73.2	72.3

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

For co-habiting individuals, spousal income appears, at first glance, to exert little influence on their ability to exit the Live Register (Table 4.2), but some more distinct patterns emerge when the data is disaggregated by gender. While males with a spouse earning above €350 per week appear much more likely to exit to employment, the opposite appears to be the case for females. These patterns may, in part, potentially reflect social norms whereby it is less socially acceptable for a male to be supported by a higher earning spouse. However, it may also be picking up unobserved characteristic differences between males and females that are related to spousal income.

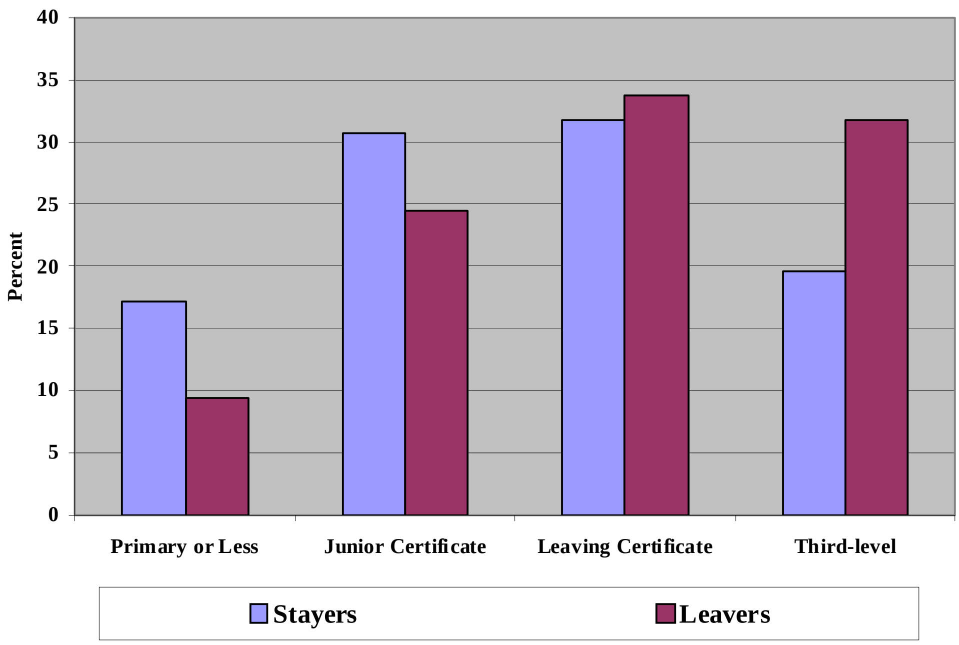
Table 4.2: Spousal Earnings Information for Stayers and Leavers (Per Cent)

	Stayers (%)	Leavers (%)	Male Stayers (%)	Female Stayers (%)	Male Leavers (%)	Female Leavers (%)
Spousal Earnings:						
≤€250.00	*3.5*	*3.3*	*2.7*	*4.5*	*2.9*	*3.9*
€251.00 - €350.00	*0.5*	*0.6*	*0.7*	*0.3*	*0.8*	*0.3*
€351.00 and Above	*17.2*	*17.2*	*5.4*	*32.9*	*9.4*	*28.0*
No Spousal Earnings	*78.8*	*78.9*	*91.2*	*62.3*	*86.9*	*67.9*
Total:	100.0	100.0	100.0	100.0	100.0	100.0

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS).

A clear expectation is that individuals with higher levels of educational attainment are more likely to be successful in obtaining employment and, indeed, this does appear to be borne out by the data. Leavers are much more likely to hold Third-level qualifications and are less likely to be educated to Primary or Junior Certificate levels (Figure 4.1). The distinction is particularly marked at both extremes of the distribution. Over 15 per cent of stayers had no formal qualifications compared to less than 10 per cent of leavers, while just over one-third of leavers held Third-level qualifications compared to just over 20 per cent of stayers. Given the well documented importance of human capital accumulation to labour market success, it is likely that these differences will prove significant when we come to formally estimate the profiling model.

Figure 4.1: Education Profile of Stayers' and Leavers' (Per Cent)



Source: Profiling Questionnaire.

Table 4.3 shows the recent unemployment histories of leavers and stayers. While leavers were more likely to have made a claim for unemployment benefit in the previous 5 years, they were much less likely to have experienced a spell of long-term unemployment in the same period, 9 per cent compared to 23 per cent of stayers. With respect to benefit type, those making claims for JB were more heavily represented among the leavers group, which is indicative of the fact that claimants with a more recent attachment to the labour market, by virtue of the fact that they had sufficient national social insurance contributions (i.e. PRSI) to qualify for JB, were more likely to exit to employment. Finally, stayers tended to be also claiming for other forms of social welfare benefit, for example, Family Income Supplement (FIS), which would have the effect of raising the lowest wage that such individuals would be willing to accept for labour market entry.[69]

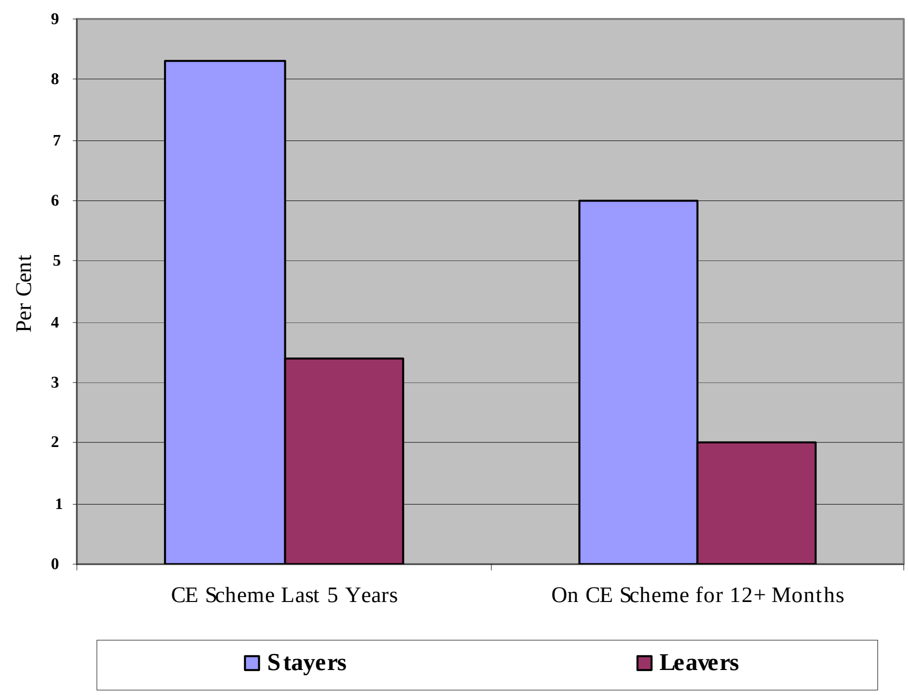
Table 4.3: Unemployment Benefit/Scheme Information on Stayers and Leavers (Per Cent)

	Stayers (%)	Leavers (%)
UE Claim in the Last 5 Years	62.1	64.2
UE Claim in the Last 5 Years & Signing on for 12+ Months	22.7	9.0
Jobseeker's Allowance (JA)	42.9	26.1
Jobseeker's Benefit (JB)	52.2	71.3
Number of Claims	1.0	1.0

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

There are also other indications in the data that those remaining on the Live Register for twelve months or more are, in general, likely to have a history of welfare dependence. As Figure 4.2 shows, stayers are much more

Figure 4.2: Community Employment Scheme Information on Stayers and Leavers (Per Cent)



Source: Profiling Questionnaire.

[69] Reservation wage.

likely to have accessed the CE scheme and to have stayed on the scheme for 12 months or longer, which again demonstrates a recent history of long-term unemployment.

The profiling questionnaire also asked respondents to give details of their recent employment history. Once more the results, which are presented in Table 4.4, show that leavers have a more recent history of labour market attachment. Leavers were much more likely to have been employed in the month previous to making their unemployment claim, 60 per cent compared to 46 per cent of stayers. With respect to the duration of the most recent spell of employment, there is no clear indication that the patterns are significantly different across the leavers and stayers populations. Finally, leavers were more prepared to consider moving for employment reasons; however, while this may be taken as an indication of higher motivation levels, it is also likely to be correlated with other characteristics such as age, marital status and family responsibilities.

Table 4.4: Employment History and Job Duration Information on Stayers and Leavers (Per Cent)

	Stayers (%)	Leavers (%)
Employment History:		
Still in Employment	*10.1*	*13.4*
Employed in Last Month	*46.3*	*60.2*
Employed in Last Year	*20.4*	*17.4*
Employed in Last 5 Years	*12.6*	*5.0*
Employed Over 6 Years Ago	*3.6*	*0.7*
Never Employed	*7.0*	*3.3*
Total:	100.0	100.0
Current/Previous Job Duration:		
Less than Month	*6.1*	*6.2*
1-6 Months	*24.7*	*30.6*
6-12 Months	*12.7*	*15.1*
1-2 Years	*11.6*	*11.4*
2 Years or More	*35.8*	*33.1*
Never Employed	*9.1*	*3.6*
Total:	100.0	100.0
Would Consider Moving for a Job	32.3	41.7

Source: Profiling Questionnaire.

Table 4.5 considers the geographical distribution of leavers and stayers. Regional analysis such as this is important as it accounts for differences in levels of local labour market demand as, all other things being equal, we might expect individuals in closer proximities to larger labour markets to have a higher incidence of exit. However, the results suggest that this may not necessarily be the case within the Irish context. With respect to labour market size, there is no discernable difference between leavers and stayers, suggesting that access to a large hub of employment is not a major factor in determining exit. Exactly why exit rates are not substantially higher among individuals located in large towns and cities is unclear; it is possible that unobserved social factors are at play here. For example, it may be the case that within an urban setting unemployed persons tend to be more heavily concentrated within areas of economic and social deprivation where welfare dependence has higher levels of acceptance, and that such factors tend to counter the positive aspects of labour market demand. Analysis at the county-level also revealed that there were no large differences in the distribution of leavers and stayers (Table 4.5).

Table 4.5: Location Information on Stayers and Leavers (Per Cent)

	Stayers (%)	Leavers (%)
Location Size:		
Rural	*25.5*	*27.4*
Village	*12.6*	*12.3*
Town	*22.9*	*22.1*
Large Town/City	*38.7*	*38.0*
Total:	100.0	100.0
Geographic Location:		
Carlow	*1.4*	*1.4*
Cavan	*2.0*	*1.2*
Clare	*2.8*	*2.9*
Cork	*11.0*	*10.7*
Donegal	*6.6*	*5.8*
Dublin	*19.4*	*20.1*
Galway	*5.3*	*5.2*
Kerry	*5.9*	*7.6*
Kildare	*2.7*	*3.2*
Kilkenny	*1.2*	*1.4*
Laois	*1.7*	*1.6*
Leitrim	*0.7*	*0.7*
Limerick	*3.8*	*4.6*
Longford	*1.1*	*0.7*
Louth	*3.5*	*3.2*
Mayo	*3.4*	*3.3*
Meath	*2.6*	*2.5*
Monaghan	*1.3*	*1.4*
Offaly	1.9	1.6
Roscommon	*0.8*	*1.0*
Sligo	*1.8*	*1.2*
Tipperary	*4.1*	*4.6*
Waterford	*3.8*	*3.8*
Westmeath	*2.7*	*2.7*
Wexford	*5.6*	*5.0*
Wicklow	*3.0*	*2.8*
Total:	100.0	100.0

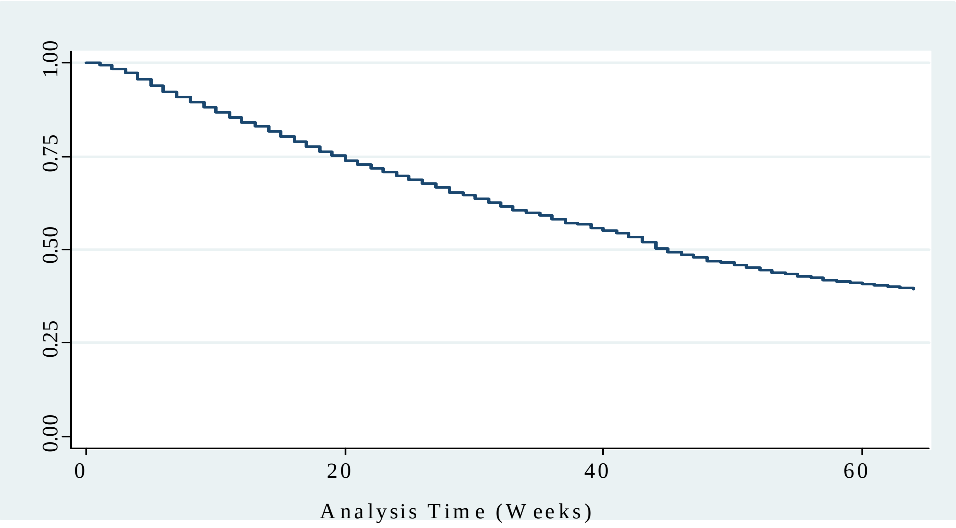
Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

4.3 Unemployment Duration and Rate of Exit from Unemployment

Finally, in this section we examine the relationship between unemployment claim duration and the rate of exit to the labour market from the Live Register. As stated, we ignore non-labour market claim closures. Consequently, duration is estimated as the period of time between an individual first appearing on the Live Register system and the week his/her claim was closed to the labour market.

Figure 4.3 plots the Kaplan-Meier (KM) survivor function; the KM calculates the fraction of individuals exiting to the labour market during successive weeks on the Live Register. The rate of exit from unemployment appears relatively constant until around week 40 at which point the curve begins to flatten somewhat. After week 55 the exit rate becomes lower again, with the KM relatively flat after this point. This indicates that the probability of a successful labour market exit from week 55 onwards has declined substantially.[70]

Figure 4.3: Kaplan-Meier Survival Function: Exits to Labour Market



[70] See Appendix B for the six and fifteen month models KM survivor functions.

5. ECONOMETRIC ANALYSIS

5.1 Introduction

While the bivariate analysis undertaken in Chapter 4 was informative, one of the main disadvantages of such an analysis is that it only reveals associations between Live Register exits and one characteristic of interest (e.g. education) at a time. Consequently, such a descriptive analysis ignores correlations between other characteristics, as well as the possibility of the simultaneous association of exit rates with more than one characteristic. The present chapter addresses this issue by using the profiling data discussed in Chapter 3 of the report to estimate our twelve month statistical profiling model, via multivariate regression methods. The results for our six and fifteen month models are presented in Appendix C, with a brief comparison of the models provided at the end of this chapter.

5.2 Statistical Profiling Model

In developing a profiling model the dependant variable used will be determined by the objectives of the profiling project, a decision that is taken by the relevant authority in charge of profiling (Hasluck, 2008). For instance, in the United States, where the principal concern relates to exhaustion of unemployment insurance (UI), the dependent variable is generally the period remaining to exhaustion. In the case of Ireland, where the policy focus is on the risk of falling into long-term unemployment, the dependant variable in this study reflects the risk of remaining unemployed for more than 52 weeks (i.e. twelve months).

When developing profiling models, two estimation strategies emerge as being dominant in the literature. The first involves logit or probit models where the dependant variable is binary (0,1), taking the value of 1 if the individual is unemployed for a certain amount of time, for example twelve months, and zero otherwise. The second approach relates to duration models which can, for simplicity, be viewed as regression models where the dependant variable is continuous and relates to time. In the case of profiling, this time variable typically relates to the number of weeks an individual remains dependent on unemployment payment before exiting to the labour market. In terms of those countries or regions that have implemented profiling systems, while some tend not to disclose information on their modelling approach, the majority of those that have appear to favour the use of probit or logit models (i.e. a binary dependent variable), specifically the two countries with the longest experiences of profiling – the United States and Australia. This aside, the research seems to indicate that the modelling approach adopted in profiling is not as important as the variables that are included in the model itself (see, for example, Black *et al.*, 2001).

In the current context, the use of a duration model is not appropriate given that the question of duration itself causes some problems. If we were to adopt a duration modelling strategy then we could chose the duration of the first unemployment claim spell. However, such an approach ignores the reason underlying the closure and would result in administrative closures being grouped with those that exited to the labour market, which is clearly not appropriate. Furthermore, some labour market exits themselves may be very brief and, thus, there are grounds for merging duration spells in some instances. The question of re-entrants with longer exit spells causes a further problem. As the decision rule adopted with respect to duration will impact strongly on the estimated model, the duration approach is associated with potentially more error than binary dependent type models (i.e. a logit or probit model). Consequently, as there is no convincing evidence for the use of one methodological approach over the other, and on the basis of common international practise and the aforementioned complications determining duration spells from the Live Register, we focus on the binary outcome variable in this study and, therefore, implement a probit model.

From a methodological perspective, we estimate separate models for both males and females on the grounds that the marginal impact of various characteristics, such as having children or spousal income, are likely to vary substantially according to gender.

Finally, before presenting our results, the following factors are included in our twelve month profiling model to predict those at risk of staying on the Live Register for 52 weeks or more: age; marital status; education; apprenticeship training; literacy/numeracy problems; English proficiency, health; size of local labour market; geographic location; own transport; access to public transport; employment history; casual employment status; job duration; willingness to move for a job; previous unemployment claim history; participation in CE scheme; benefit type; number of claims and spousal earnings.[71] As indicated earlier in the report, information on these covariates came from the questionnaire that was administered to all claimants and also from the Live Register administrative database (ISTS).

5.3 Results: Twelve Month Models

To begin with both the male and female twelve month profiling models are well specified, with the vast majority of the variables behaving as expected. The marginal effects presented for each model in Table 5.1 describe the impact of each of the covariates on the probability of a claimant leaving the Live Register for the labour market after 52 weeks, holding the other factors that are included in the model constant.[72]

5.3.1 Male Model

Turning first to the results of the male model, perhaps not surprisingly, the most important predictors of their future long-term unemployment relate to the individual's unemployment history, with those who had signed on for more than 12 months in the last 5 years 17 per cent less likely to exit

[71] The same explanatory variables are used in the six and fifteen month profiling models.
[72] In the modelling, we do not use interaction terms on the basis that these will affect the individual level terms which will in turn have an impact on the predicted probability of an individual who is not affected by both attributes.

before 52 weeks. Males with previous participation in the CE scheme also had a reduced likelihood of avoiding long-term unemployment. This finding would tend to support the findings of a recent OECD study that questioned the effectiveness of the CE scheme as an intervention to enhance participants' subsequent employment prospects (OECD, 2009). While most of the unemployment related variables were associated with a higher probability of long-term welfare dependence, there was one exception. Relative to the omitted category of males who had not made an unemployment claim in the previous 5 years; those who had but were unemployed for less than 12 months were less likely to remain welfare dependant for more than 52 weeks. This is somewhat counterintuitive. However, it seems most likely that the unemployment spells of this group were of a relatively short duration, which suggests that a history of short-term unemployment leads to a higher propensity for labour market entry. Nevertheless, some finer detail on the question relating to the duration of previous unemployment spells would be necessary to confirm this.

Age was another factor that was found to be an important predictor of long-term unemployment for males. Specifically, relative to those aged under-25 years, the decline in the probability of exiting welfare assistance before week 52 ranged from 3 per cent for those aged 35-44 years to 22 per cent for persons aged 55 years or over. Health status was also a key indicator. Relative to the base case of poor or very poor health, claimants reporting good or very good health were 10 and 13 per cent more likely to exit to the labour market respectively.

Some family background characteristics were also important. While married males were more likely to find employment, those with children tended to have lower exit probabilities, which again may reflect a higher reservation wage. In addition, males whose partners earned above €350 or below €250 per week were more likely to exit to the labour market prior to the 52 week time point.

Education emerged as another significant predictor of long-term unemployment for males. Compared to individuals with primary-level schooling only, holders of third-level qualifications and Leaving Certificates were less likely to be unemployed for more than 12 months, by 11 and 6 per cent respectively. The margin of advantage fell to zero for those educated to Junior Certificate level. With respect to the more basic educational attributes that the profiling questionnaire asked respondents about, their numeracy/literacy and English language skills, English proficiency was found not to act as a barrier to successful labour market entry. However, claimants reporting literacy or numeracy problems were 7 per cent more likely to remain welfare dependant for a period in excess of 52 weeks. This result confirms the view that a lack of basic skills remains a substantial barrier to successful labour market participation.

Access to transport and a willingness to move also affected a male's likelihood of remaining unemployed after 12 months. Having access to ones own transport increased the probability of a successful labour market exit by 6 per cent, while those who expressed a willingness to relocate for employment purposes were 4 per cent more likely to find a job. Access to public transport, however, did not prove to be as important a factor for males.

Consistent with the descriptive analysis, males with more recent attachments to the labour market i.e. those on JB or recently/currently employed had a higher probability of leaving the Live Register prior to 52 weeks. Those casually employed were some 9 per cent more likely to remain welfare dependant for twelve months or more. While employment of this nature may have the objective of facilitating a successful transition off the Live Register to more stable employment, this result indicates that it does not in fact achieve this outcome.

Finally, with respect to location, relative to those living in smaller rural areas, males located in towns and cities were approximately 4 to 6 per cent more likely to remain welfare dependant after 12 months, a result which suggests that ready access to large local labour markets is of little advantage in the Irish context. Regarding specific county effects, relative to Dublin exit rates were lower among males located in Longford, Cavan, Sligo, Galway, Donegal, Mayo, Cork, Offaly and Wexford.

5.3.2 Female Model

In relation to the female twelve month profiling model, the results were very similar to those for males with successful labour market exit rising with third-level education, recent employment, a willingness to move for a job and good health. In addition, the probability of leaving the Live Register before 52 weeks fell with number of children, literacy/numeracy difficulties, a history of unemployment and casual employment status. However, some differences are apparent between the two gender models. Relative to single persons, females who are married or separated are less likely to enter the labour market before 52 weeks, as were those whose spouse was a high earner. The magnitude of the impact of children on labour market entry was also higher for females. These three specific results largely reflect the higher tendency of females to undertake family responsibilities which, in turn, may reduce their ability or preference to find employment. Another significant gender difference is that those in receipt of JA were more likely to remain welfare dependant relative to those on either JB or contributions only assistance. Furthermore, the number of additional welfare claims received by females emerged as another significant impediment to their exiting the Live Register before 12 months.[73] Regarding location, unlike males, females appear to derive no disadvantage from living in an urban location. Finally, with respect to specific county effects, relative to Dublin, exit rates were lower for females living in Cavan, Longford, Offaly, Sligo, Wexford, Meath, Donegal, Cork, Leitrim, Westmeath and Louth.

[73] However, it is important to note that only a very small proportion of females have multiple active claims.

Table 5.1: Marginal Effects for Binary Probit Models of Male and Female Claimants Leaving the Live Register After Twelve Months

Variable	**Males**	**Females**
Personal and Family Characteristics:		
Age Reference Category: Aged 18-24		
Aged 25-34 Years	-0.031***	-0.034**
	(0.012)	(0.016)
Aged 35-44 Years	-0.091***	-0.049***
	(0.014)	(0.018)
Aged 45-54 Years	-0.110***	0.013
	(0.016)	(0.019)
Aged 55+ Years	-0.216***	-0.069***
	(0.019)	(0.022)
Health Reference Category: Bad/Very Bad Health		
Very Good Health	0.128***	0.332***
	(0.039)	(0.047)
Good Health	0.098**	0.253***
	(0.038)	(0.042)
Fair Health	0.019	0.153***
	(0.040)	(0.047)
Marital Status Reference Category: Single		
Married	0.026**	-0.072***
	(0.013)	(0.017)
Cohabits	-0.020	-0.000
	(0.032)	(0.037)
Separated/Divorced	-0.018	-0.083***
	(0.026)	(0.032)
Widowed	0.043	-0.057
	(0.053)	(0.041)
Children	-0.030***	-0.060***
	(0.006)	(0.010)
Spousal Earnings Reference Category: None		
Spouse Earnings €250	0.057**	0.014
	(0.023)	(0.025)
Spouse Earnings €251-€350	0.009	-0.032
	(0.044)	(0.084)
Spouse Earnings €351+	0.029*	-0.101***
	(0.017)	(0.017)
Human Capital Characteristics:		
Education Reference Category: Primary or Less		
Junior Certificate	0.002	0.004
	(0.012)	(0.018)
Leaving Certificate	0.063***	0.034*
	(0.012)	(0.018)
Third-level	0.114***	0.125***
	(0.013)	(0.018)
Apprenticeship	0.037***	-0.015
	(0.010)	(0.018)
Literacy/Numeracy Problems	-0.066***	-0.061**
	(0.015)	(0.025)

Table 5.1: Marginal Effects for Binary Probit Models of Male and Female Claimants Leaving the Live Register After Twelve Months (Continued)

Variable	Males	Females
English Proficiency	-0.034	0.001
	(0.023)	(0.032)
Employment/Unemployment/Benefit History:		
Employment History Reference Category: Never Employed		
Still In Employment	0.180***	0.244***
	(0.024)	(0.027)
Employed in Last Month	0.149***	0.161***
	(0.027)	(0.033)
Employed in Last Year	0.063**	0.062*
	(0.026)	(0.033)
Employed in Last 5 Years	0.029	-0.029
	(0.028)	(0.037)
Employed over 6 Years Ago	-0.014	-0.136***
	(0.037)	(0.051)
Casually Employed	-0.094***	-0.160***
	(0.018)	(0.015)
Would Move for a Job	0.038***	0.082***
	(0.008)	(0.011)
Job Duration Reference Category: Never Employed		
Job Duration Less than Month	-0.013	0.021
	(0.027)	(0.034)
Job Duration 1-6 Months	0.011	0.069**
	(0.024)	(0.030)
Job Duration 6-12 Months	0.015	0.040
	(0.024)	(0.031)
Job Duration 1-2 Years	-0.037	0.041
	(0.026)	(0.031)
Job Duration 2+ Years	-0.065***	0.020
	(0.024)	(0.031)
UE Claim Previous 5 years	0.044***	0.126***
	(0.009)	(0.010)
Signing for 12 months+	-0.166***	-0.188***
	(0.012)	(0.016)
CE Scheme Previous 5 years	-0.070***	-0.074**
	(0.027)	(0.037)
On CE Scheme for 12 months+	-0.071**	-0.145***
	(0.035)	(0.044)
Social Welfare Payment Type Reference Category: UE Credits		
Jobseeker’s Allowance	0.014	-0.115***
	(0.028)	(0.026)
Jobseeker’s Benefit	0.194***	0.093***
	(0.027)	(0.024)

Table 5.1: Marginal Effects for Binary Probit Models of Male and Female Claimants Leaving the Live Register After Twelve Months (Continued)

Variable	Males	Females
Number of Claims	-0.085	-0.332***
	(0.053)	(0.037)
Location Reference Category: Rural		
Village	-0.035**	-0.024**
	(0.015)	(0.016)
Town	-0.040***	0.006
	(0.014)	(0.015)
City	-0.055***	0.003
	(0.014)	(0.015)
Own Transport	0.058***	0.015
	(0.009)	(0.011)
Near Public Transport	0.019*	-0.030**
	(0.011)	(0.012)
County Location Reference Category: Dublin		
Cavan	-0.175***	-0.165***
	(0.036)	(0.038)
Cork	-0.033**	-0.038**
	(0.015)	(0.019)
Donegal	-0.054***	-0.054**
	(0.020)	(0.023)
Galway	-0.091***	-
	(0.020)	-
Leitrim	-	-0.110*
	-	(0.060)
Longford	-0.177***	-0.160***
	(0.042)	(0.055)
Louth	-	-0.049*
	-	(0.029)
Mayo	-0.059**	-
	(0.024)	-
Meath	-	-0.062**
	-	(0.031)
Offaly	-0.050*	-0.138***
	(0.03)	(0.039)
Sligo	-0.104***	-0.114***
	(0.033)	(0.044)
Westmeath	-	-0.052*
	-	(0.030)
Wexford	-0.039*	-0.071***
	(0.021)	(0.024)
Observations	17,738	13,024
Pseudo R^2	0.1150	0.1394

Note: Standard errors in parentheses.
* significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.
\- designates insignificant.

5.4 Twelve Month Models' Predictive Power

The next important step in developing a profiling model is to see how effective it is at accurately predicting those at risk of becoming long-term unemployed. Tables 5.2 and 5.3 describe the extent to which our twelve month gender models successfully predicted male and female leavers and stayers at various probability cut-off points.

If we take males (Table 5.2) with a probability above 0.5[74] as likely to exit to the labour market before 52 weeks (i.e. a leaver) and those with a probability below or equal to 0.5 as likely to remain on the Live Register (i.e. a stayer), overall the model will correctly identify 69 per cent of cases. Breaking this down into stayers and leavers, 65 per cent of male stayers were correctly predicted by our twelve month model, with the corresponding figure for male leavers standing at 71 per cent. The results from the female model (Table 5.3) are very similar to those of the male model, with little difference discernable between the two models in terms of their predictive power.

Table 5.2: Reliability Tests: Male Twelve Month Model

	50 Per Cent Cut-off	60 Per Cent Cut-off	70 Per Cent Cut-off	80 Per Cent Cut-off
Correctly Predicted:	12,282	9,739	6,488	2,780
Total:	17,738	13,121	8,191	3,355
Percentage (%):	0.692	0.742	0.792	0.828
Percentage of Stayers Correctly Predicted:	0.654	0.722	0.787	0.810
Percentage of Leavers Correctly Predicted:	0.706	0.747	0.793	0.832

So how do we rate this performance? If we were to take a random draw of 100 persons from our sample and classify them as stayers, based on our distribution, it is likely that we would correctly identify 39 persons, and if we were to do the same for leavers the figure would be 61 individuals, giving a predictive measure of 50 per cent (39+61/200). Therefore, our male and female statistical profiling models outperform a random draw by a substantial margin at the 0.5 cut-off point.

As the cut-off point for identifying those at risk of falling into long-term unemployment is increased from 0.5 to 0.6 to 0.7 to 0.8 the accuracy of our models improve further. At the 0.8 cut-off point (i.e. the group estimated to have an 80 per cent chance of staying on the Live Register), the overall accuracy of the male and female models are 83 and 85 per cent respectively (Tables 5.2 and 5.3). Therefore, at this cut-off point, 81 per cent of males and 87 per cent of females that were earmarked as stayers were correctly identified. It is important to note that as the cut-off point is raised not only is there an efficiency gain, whereby the model identifies an increasing proportion of stayers relative to what would be achieved through a random draw, there also exists an equity gain. The equity gain relates to the fact that

[74]The cut-off point used for identifying those at risk of falling into long-term unemployment is 0.5.

at higher cut-off points those individuals identified will be increasingly high risk, in terms of their probability of becoming long-term unemployed, and, consequently, the likelihood that public resources will be expended on those individuals most in need of assistance increases rapidly.

Table 5.3: Reliability Tests: Female Twelve Month Model

	50 Per Cent Cut-off	60 Per Cent Cut-off	70 Per Cent Cut-off	80 Per Cent Cut-off
Correctly Predicted:	9,088	7,299	5,062	2,516
Total:	13,024	9,668	6,239	2,949
Percentage (%):	0.698	0.755	0.811	0.853
Percentage of Stayers Correctly Predicted:	0.664	0.743	0.818	0.874
Percentage of Leavers Correctly Predicted:	0.711	0.759	0.810	0.850

In terms of international comparisons, unfortunately, as indicated in Section 2.7, most countries do not release specific details on their model's predictive power, or on the exact specification that lies behind it. However, some information on the predictive performance of Denmark's model is available in Rosholm *et al.* (2006), which provides some benchmark against which to compare the profiling model generated here for Ireland. The Danish model is estimated at a six month point, thus, the assessment undertaken here relates to our six month model as opposed to the twelve month. At the 0.5 per cent cut-off point, the Danish model reports a percentage correctly predicted figure of 66 per cent, which suggests that our six month models perform (which achieve 68 and 69 per cent correct predictions for male and female models respectively) marginally better than its Danish counterpart. Rosholm *et al.* (2006) also found that the Danish male model had a higher predictive power than the female model.[75] We find that our female model performs slightly better than the male model. However, the difference is marginal and not likely to be statistically significant.

Figures 5.1 and 5.2 show the distribution of predicted welfare dependence probabilities among both males and females.[76] The male distribution appears quite normal (Figure 5.1), with relatively few cases associated with a predicted probability in excess of 80 per cent. This suggests that the cut-off point for identifying those at risk of falling into long-term unemployment could be set below this without incurring a substantial increase in the number of persons sent for immediate interventions. However, the female distribution is much more bimodal in nature (Figure 5.2), with a much larger proportion of females' assigned probabilities in excess of 80 per cent. This result implies that the cut-off point for female intervention should be set somewhat above that of males. However, the final decision on the most appropriate cut-off point for immediate intervention will ultimately be a matter for policymakers and will depend crucially on their objectives and resources.

[75] See Section 2.7 for more details.

[76] See Appendix D for six and fifteen month model figures.

Figure 5.1: Distribution of Male Welfare Dependence Probabilities

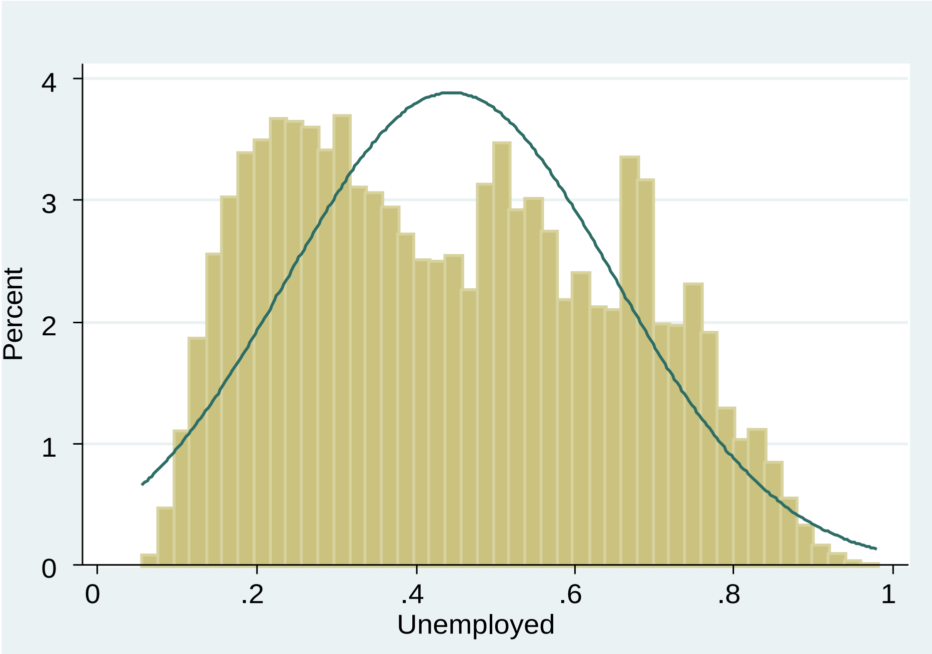
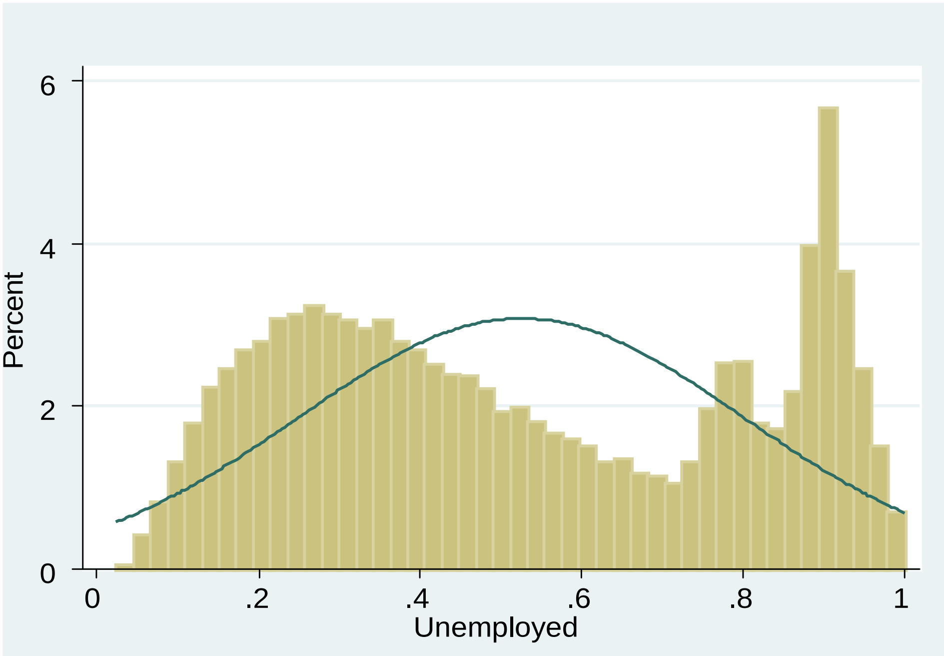


Figure 5.2: Distribution of Female Welfare Dependence Probabilities



5.5 Comparison of Six, Twelve and Fifteen Month Profiling Models

Tables C1 and C2 in Appendix C present the results from our three profiling models – three, six and twelve month models – for both males and females respectively. The first point to note is that the three models are well specified. Second, the marginal effects are relatively stable over time. In particular, the key characteristics that emerged in the twelve month model as being significant predictors of a claimant's probability of falling into long-term unemployment also arise in the six and fifteen month models. Thus, the main factors that determine whether or not an individual becomes long-term unemployed, in an Irish context at least, are as follows: (i) having a history of long-term unemployment;[77] (ii) previous participation on the CE scheme, and remaining on the scheme for more than twelve months; (iii) being casually employed; (v) a lack of basic literacy and numeracy skills; and (vi) a claimant's geographic location. Conversely, (i) high levels of educational attainment; (ii) having good health; and (iii) being recently attached to the labour market reduces the likelihood that an unemployment claimant becomes long-term unemployed. Clearly, some of the aforementioned predictors of long-term unemployment can be addressed through the introduction of appropriate policy measures.

Some interesting gender differences exist regarding the factors that determine whether or not an unemployment claimant becomes long-term unemployed. Specifically, having children is a bigger barrier for female claimants than it is for males. In contrast, being older has a larger negative impact on a male's likelihood of leaving the Live Register. Having a spouse that earns in excess of €351 per week is another factor that reduces a female's likelihood of leaving the Live Register, whereas the opposite result holds for a male claimant, albeit the effect is small. The number of additional welfare payments that a female receives is also a strong predictor of their long-term unemployment prospects; however, this factor only becomes significant from the twelve month point onwards. For males, the number of additional payments that they receive only arises as an impediment to exiting to the labour market in the six month model. Another factor that emerges as being an important predictor of long-term unemployment for females but not males is receipt of JA. On the other hand, living in an urban location is a barrier to males leaving the Live Register but is not for females. All of these factors are relatively consistent predictors of long-term unemployment across the three time points.

[77] 'Signing on for 12 months+' variable in Tables C1 and C2.

6. SUMMARY AND CONCLUSION

6.1 Introduction

This report outlines the results of the Irish six, twelve and fifteen month profiling models, using data that tracks the progress of claimants over a period ranging from 26 to 78 weeks following their initial claim. The data used for the modelling came from both the Live Register administrative database and a specially designed questionnaire issued to all individuals making a claim for unemployment benefit over a 13 week period (September to December 2006), during which our claimant population was constructed.

The statistical profiling models, for both males and females, which were estimated from these data, are very well specified. The results from the male model, for the three time-points, indicate that the probability of remaining on the Live Register is associated with a recent history of long-term unemployment; previous participation on the Community Employment (CE) scheme; advanced age; number of children; relatively low education; literacy/numeracy problems; located in urban areas; a lack of personal transport; low levels of recent labour market attachment; spousal earnings and geographic location. The results from the female model are broadly similar to those of males with successful labour market exit rising with third-level education, recent employment, a willingness to move for a job and good health, while the probability of remaining on the Live Register increases with number of children, literacy/numeracy difficulties, a history of unemployment and casual employment status. However, some gender differences are apparent. In particular, females who are married or separated are less likely to leave the Live Register, as are those whose spouse is a high earner. The magnitude of the impact of children on labour market entry is also higher for females. Regarding location, unlike males, females appear to derive no disadvantage from living in an urban location.

In terms of predictive power, out of all of the countries whose profiling models were analysed only Denmark released specific details on its model's predictive power, which is a six month model: the equivalent Irish model was found to outperform the six month profiling model that has been implemented in Denmark. The main Irish model is particularly accurate in predicting outcomes at 12 months in respect of high-risk individuals: at the 80 per cent cut-off point (i.e. the group estimated to have an 80 per cent chance of staying on the Live Register) the overall accuracy of the model is 83 per cent of cases predicted correctly among males and 85 per cent correct among females.

6.2 Profiling in the Recession

There has been a very severe deterioration in the Irish labour market over the past year or so, with a dramatic increase in unemployment. For example, the seasonally adjusted number on the Live Register increased from 179,600, in January 2008 to 326,100 in January 2009, while the standardised unemployment rate increased from 4.8 per cent to 9.6 per cent over the same period (CSO, 2009). How does this dramatic change in labour market conditions affect the accuracy of the profiling model, given that the model is based on movements on and off the Live Register between the fourth quarter of 2006 and the first quarter of 2008, when labour market demand was a good deal more buoyant? While the recession, entailing both a contraction in employment and a growth in unemployment, will lead to longer spells of unemployment for most jobseekers, it is unlikely to alter relative probabilities of long duration in unemployment. The profiling model identifies those jobseekers with a very high probability of becoming long-term unemployed. The recession may increase the probability that disadvantaged job-seekers will become long-term unemployed and lead to longer spells in unemployment, but it will not appreciably alter their probabilities relative to other, more advantaged job-seekers. The profiling model also indicates the personal characteristics that are associated with a high probability of long-term unemployment. As outlined above, these include low education, literacy and/or numeracy difficulties, advanced age, and a record of recent unemployment, among other characteristics. Such characteristics can also be expected to determine labour market prospects during a recession, and individuals suffering such multiple disadvantages will continue to have very high probabilities of long spells of unemployment.

The key outcome of the profiling model is a probability score that indicates the likelihood of leaving the Live Register to take up employment. This can also be regarded as a rank ordering of individuals in terms of their probability of remaining unemployed, and therefore their need of assistance. A rapid increase in the numbers becoming unemployed, as has occurred in recent months, generates severe pressure on the capacity of the Public Employment Service (PES) to cope with increased demands for services and access to active labour market policies to assist unemployed jobseekers to get back to work. Currently, for example, under the National Employment Action Plan, job-seekers who have been unemployed for 3 months are referred by the DSFA to FÁS for assistance. It is difficult to envisage how the PES can cope with such a universal approach to activation with a very large increase in the numbers to be activated. Furthermore, it is wasteful to refer all clients for such intervention, given that we know that many can find jobs on the basis of their own resources and efforts. An additional advantage of the profiling system is that it provides a systematic basis for identifying those most in need of interventions, and, thus, a fair and rational basis for allocating scarce resources to those most in need. With profiling, we can adjust the intervention threshold to match available resources: when the absolute number of clients increases, the threshold value (probability score) can be increased to ensure that available resources are allocated to those with the highest probability of experiencing difficulty in getting back to work.

6.3 System Maintenance: Up-dating and Enhancing the Profiling Model

The profiling model that we have estimated for Ireland indicates that the risk of long-term unemployment is heavily determined by enduring human capital characteristics, such as age, education, literacy and/or numeracy, and previous labour market history. The impact of these factors is very likely to remain stable over time and in changing economic circumstances. However, profiling should not be regarded as a once-off operation: it requires continuous assessment and updating to ensure that accuracy levels are maintained and improved. It is good practice to update the model to take account of changing economic conditions, as is practiced in the Australian system (Lipp, 2005).

Provision for system maintenance – including updating, enhancement and monitoring activation – can be integrated into the profiling system itself if the relevant data on individual characteristics and Live Register outcomes are collected and stored in a format appropriate to allow retrieval for analysis. There are three key elements to maintaining the system:

1. *Up-dating the model.* It is good practice to update the model to take account of changing economic conditions, as happens in the Australian system (Lipp, 2005). Wadner and Messenger (1999) in their evaluation of the US profiling model recommend that the model should be up-dated to take account of changing circumstances every 3 years or so.

2. *Enhancing the model.* It would also be useful to examine whether the accuracy of the model can be increased by the inclusion of additional predictive variables. In the Irish case, three additional variables could prove useful: occupation, sector and earnings related to most recent employment. Occupation is collected as part of the administrative system in the Live Register, but at present, this can relate to the client's occupation when an individual first makes an unemployment related claim, is not necessarily updated at most recent claim, and therefore, in some instances, can be very dated historical information. It would be straightforward to incorporate these variables into the initial data- capture phase of the proposed profiling system.

3. *Monitoring activation programmes.* As discussed at the outset of this report, the success of profiling crucially depends on the delivery of targeted activation programmes that effectively enhance the employment prospects of their participants. This would require recording of the intervention programmes delivered to those individuals who have been identified by the profiling system as at high risk and tracking their subsequent outcomes on the Live Register and in the labour market.

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APPENDIX A: SIX AND FIFTEEN MONTH PROFILING MODELS' SAMPLE INFORMATION

SIX MONTH MODEL SAMPLE INFORMATION

The initial unemployment benefit claimant sample for the six month model was 33,754 cases.[78] Of this group, 14,673 had their claims closed after six months and 19,081 were still signing-on the Live Register.

As in the twelve month model, we defined a closure to the labour market (i.e. a leaver) in the six month model as an individual whose original claim had closed because he/she had either: (i) signed off and were gone to work; (ii) failed to sign-on; or (iii) were gone abroad.[79] Thus, of the original 14,673 leavers, 12,205 had exited to the labour market at the end of six months. A further 1,162 had unknown reasons for closure and were excluded from the study,[80] while the remaining 1,306 cases were reassigned as stayers as these individuals had closed their initial unemployment claim but had transferred to another type of benefit, thus, they continued to be welfare dependent.

In the six month model we ignored the possibility that an individual's original claim may have closed as a result of a successful exit to the labour market and that they subsequently had another unemployment claim activated and, therefore, re-entered the system (i.e. we ignore re-entrants). This is because the issue of re-entry is a more significant factor in the twelve and fifteen month models than it is in the six month model.

After these adjustments, the final unemployment claimant population used in the six month model consisted of 32,592 cases, 12,205 of which were labour market exit individuals and the remaining 20,387 were stayers. This information is summarised in Table A1.

[78] The initial unemployment benefit claimant sample (33,754) is the same for the three profiling models.
[79] Same definition that is used in the twelve and fifteen month profiling models.
[80] Reduces original sample to 32,592.

Table A1: Six Month Model Leavers' and Stayers' Sample Information

Profiling Data	**Numbers**
Original Population	60,189
Exclusions:	
- Duplicates	*1,164*
- None JA and JB Claims	*1,863*
	57,162
Questionnaire Information	44,075
JA and JB Claims:	33,754
- Leavers at 6 Months	*14,673 (44%)*
- Stayers at 6 Months	*19,081 (56%)*
Leavers' Sample Adjustments:	
1. Welfare Dependent Leavers Redefined as Stayers	1,306
2. Unknown Reason for Closure Cases Eliminated from Sample	1,162
Final JA and JB Claims Sample:	***32,592***
- Final Leavers' Sample at 6 Months	12,205 (37%)
- Final Stayers' Sample at 6 Months	20,387 (63%)

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

FIFTEEN MONTH MODEL SAMPLE INFORMATION

As with the six and twelve month profiling models, the fifteen month model started off with an original sample of 33,754 unemployment benefit claimants. At the end of fifteen months, 20,599 of these individuals had their claims closed with the remaining 13,155 continuing to be welfare dependent.

In relation to our leavers sample adjustments, of the original 20,599 leavers at the fifteen month point, (i) 14,766 had exited to the labour market; (ii) 2,458 cases had closed their claims for some unknown reasons and, consequently, were eliminated from the analysis,[81] and (iii) 3,375 had closed but not to the labour market. The majority of this latter group (3,375) had either exhausted their Jobseeker's Benefit (1,402), had transferred to general benefits (948) or were overdue signatures (348). Thus, this group of non-labour market closures were reassigned as stayers.

In terms of our stayers' sample, 5,032 of this group were active in the labour market in either the six or twelve month profiling model, thus, they were redefined as leavers. A further 171 re-entrants (i.e. individuals that had exited to the labour market for a substantial period, defined here as more than six weeks, before re-entering) were also reassigned as leavers to the labour market, on the basis that the reason that they gave for closing their claim, prior to the substantial period that they had spent off the Live Register, was to take up a job. Another 829 of these re-entrant cases were dropped from the analysis[82] as they had an unknown reason for closure when they left the Live Register for a large period of time.

[81] Reduces original sample to 31,296.
[82] This results in a final fifteen month model sample of 30,467 cases.

These leaver and stayer sample adjustments, which are summarised in Table A2, gave rise to a final fifteen month model leaver sample of 19,627 cases and 10,840 stayers.

Table A2: Fifteen Month Model Leavers' and Stayers' Sample Information

Profiling Data	**Numbers**
Original JA and JB Claims Sample:	33,754
- Leavers at 15 Months	20,599 (61%)
- Stayers at 15 Months	13,155 (39%)
Leavers' Sample Adjustments:	
1. Welfare Dependent Leavers Redefined as Stayers	3,375
2. Unknown Reason for Closure Cases Eliminated from Sample	2,458
3. Leavers with 65 Plus Weeks of UE Duration Redefined as Stayers	171
Stayers' Sample Adjustments:	
1. Stayers Redefined as Leavers	5,032
2. Unknown Reason for Closure Cases Eliminated from Sample	829
Final JA and JB Claims Sample:	30,467
- Final Leavers' Sample at 15 Months	19,627 (64%)
- Final Stayers' Sample at 15 Months	10,840 (36%)

Source: Department of Social and Family Affairs, Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

APPENDIX B: SIX AND FIFTEEN MONTH PROFILING MODELS' KAPLAN-MEIER SURVIVAL FUNCTIONS

Figure B1: Six Month Model Kaplan-Meier Survival Function: Exits to Labour Market

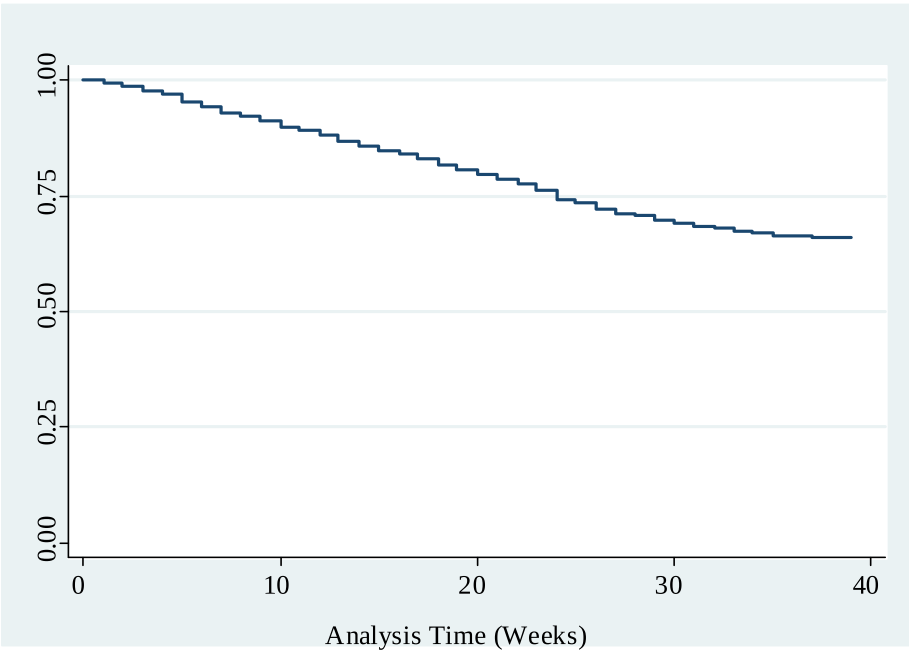
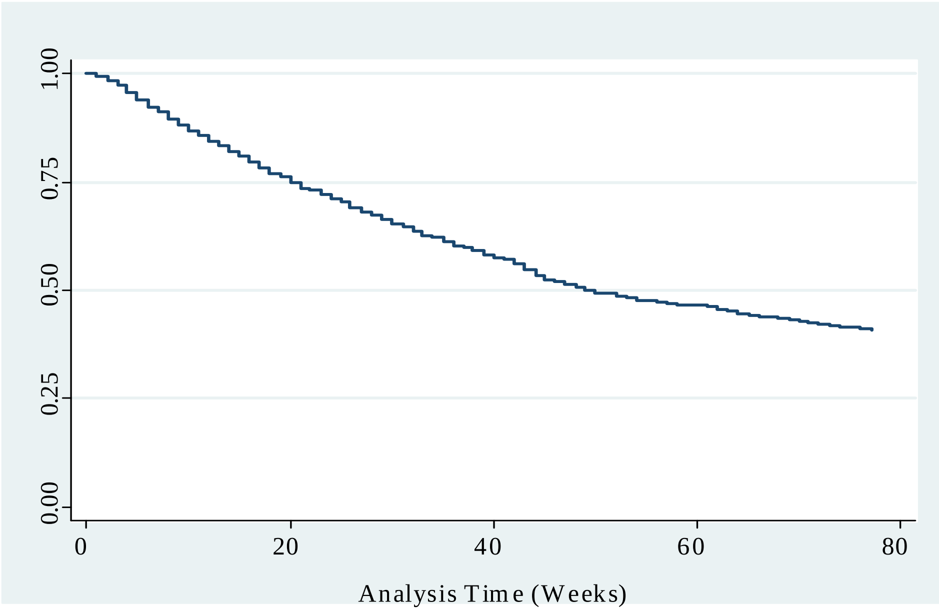


Figure B2: Fifteen Month Model Kaplan-Meier Survival Function: Exits to Labour Market



APPENDIX C: SIX, TWELVE AND FIFTEEN MONTH PROFILING MODELS' RESULTS

Table C1: Marginal Effects for Binary Probit Models of Male Claimants Leaving the Live Register

Variables	**Six Month**	**Twelve Month**	**Fifteen Month**
Personal and Family Characteristics:			
Age Reference Category: Aged 18-24 years			
Aged 25-34 Years	-0.001	-0.031***	-0.035***
	(0.013)	(0.012)	(0.011)
Aged 35-44 Years	-0.062***	-0.091***	-0.096***
	(0.015)	(0.014)	(0.014)
Aged 45-54 Years	-0.087***	-0.110***	-0.117***
	(0.017)	(0.016)	(0.016)
Aged 55+ Years	-0.185***	-0.216***	-0.222***
	(0.018)	(0.019)	(0.019)
Health Reference Category: Bad/Very Bad Health			
Very Good Health	0.094**	0.128***	0.126***
	(0.047)	(0.039)	(0.037)
Good Health	0.062	0.098**	0.094***
	(0.047)	(0.038)	(0.036)
Fair Health	-0.017	0.019	0.012
	(0.049)	(0.040)	(0.038)
Marital Status Reference Category: Single			
Married	0.035**	0.026**	0.023**
	(0.015)	(0.013)	(0.013)
Cohabits	-0.013	-0.020	-0.027
	(0.036)	(0.032)	(0.031)
Separated/Divorced	-0.038	-0.018	-0.013
	(0.030)	(0.026)	(0.025)
Widowed	0.006	0.043	0.048
	(0.062)	(0.053)	(0.051)
Children	-0.027***	-0.030***	-0.027***
	(0.007)	(0.006)	(0.006)

Table C1: Marginal Effects for Binary Probit Models of Male Claimants Leaving the Live Register (Continued)

Variables	Six Month	Twelve Month	Fifteen Month
Spousal Earnings Reference Category: None			
Spouse Earnings €250	0.055**	0.057**	0.060***
	(0.027)	(0.023)	(0.022)
Spouse Earnings €251-€350	0.037	0.009	0.089
	(0.048)	(0.044)	(0.043)
Spouse Earnings €351+	0.049**	0.029*	0.032*
	(0.019)	(0.017)	(0.017)
Human Capital Characteristics:			
Education Reference Category: Primary or Less			
Junior Certificate	0.022	0.002	0.002
	(0.015)	(0.012)	(0.012)
Leaving Certificate	0.091***	0.063***	0.059***
	(0.015)	(0.012)	(0.012)
Third-level	0.165***	0.114***	0.114***
	(0.017)	(0.013)	(0.013)
Apprenticeship	0.028**	0.037***	0.041***
	(0.011)	(0.010)	(0.010)
Literacy/Numeracy Problems	-0.068***	-0.066***	-0.060***
	(0.017)	(0.015)	(0.015)
English Proficiency	-0.098***	-0.034	-0.045**
	(0.025)	(0.023)	(0.023)
Employment/Unemployment/Benefit History:			
Employment History Reference Category: Never Employed			
Still In Employment	0.157***	0.180***	0.173***
	(0.038)	(0.024)	(0.022)
Employed in Last Month	0.143***	0.149***	0.149***
	(0.032)	(0.027)	(0.027)
Employed in Last Year	0.062*	0.063**	0.065**
	(0.034)	(0.026)	(0.025)
Employed in Last 5 Years	0.009	0.029	0.036
	(0.036)	(0.028)	(0.027)
Employed over 6 Years Ago	0.002	-0.014	-0.007
	(0.047)	(0.037)	(0.035)
Casually Employed	-0.145***	-0.094***	-0.083***
	(0.017)	(0.018)	(0.018)
Would Move for a Job	0.033***	0.038***	0.035***
	(0.009)	(0.008)	(0.008)

Table C1: Marginal Effects for Binary Probit Models of Male Claimants' Leaving the Live Register (Continued)

Variables	**Six Month**	**Twelve Month**	**Fifteen Month**
Job Duration Reference Category: Never Employed			
Job Duration Less than Month	-0.001	-0.013	0.002
	(0.033)	(0.027)	(0.026)
Job Duration 1-6 Months	0.020	0.011	0.017
	(0.029)	(0.024)	(0.023)
Job Duration 6-12 Months	0.052*	0.015	0.017
	(0.030)	(0.024)	(0.024)
Job Duration 1-2 Years	0.003	-0.037	-0.035
	(0.030)	(0.026)	(0.025)
Job Duration 2+ Years	-0.020	-0.065***	-0.053***
	(0.029)	(0.024)	(0.024)
UE Claim Previous 5 years	0.057***	0.044***	0.045***
	(0.010)	(0.009)	(0.009)
Signing for 12 months+	-0.179***	-0.166***	-0.159***
	(0.012)	(0.012)	(0.012)
CE Scheme Previous 5 years	-0.070**	-0.070***	-0.090***
	(0.031)	(0.027)	(0.027)
On CE Scheme for 12 months+	-0.108***	-0.071**	-0.053**
	(0.038)	(0.035)	(0.035)
Social Welfare Payment Type Reference Category: UE Credits			
Jobseeker's Allowance	-0.048	0.014	0.022
	(0.031)	(0.028)	(0.027)
Jobseeker's Benefit	0.142***	0.194***	0.200***
	(0.030)	(0.027)	(0.027)
Number of Claims	-0.271***	-0.085	-0.092*
	(0.090)	(0.053)	(0.051)
Location Characteristics:			
Location Reference Category: Rural			
Village	-0.024	-0.035**	-0.033**
	(0.016)	(0.015)	(0.014)
Town	-0.042***	-0.040***	-0.035***
	(0.015)	(0.014)	(0.013)
City	-0.042***	-0.055***	-0.054***
	(0.015)	(0.014)	(0.013)
Own Transport	0.085***	0.058***	0.058***
	(0.010)	(0.009)	(0.009)

Table C1: Marginal Effects for Binary Probit Models of Male Claimants' Leaving the Live Register (Continued)

Variables	Six Month	Twelve Month	Fifteen Month
Near Public Transport	0.018	0.019*	0.022**
	(0.013)	(0.011)	(0.011)
County Location Reference Category: Dublin			
Cavan	-0.121***	-0.175***	-0.158***
	(0.036)	(0.036)	(0.036)
Cork	-	-0.033**	-0.037**
	-	(0.015)	(0.015)
Donegal	-0.043*	-0.054***	-0.052***
	(0.022)	(0.020)	(0.020)
Galway	-0.067***	-0.091***	-0.089***
	(0.020)	(0.020)	(0.020)
Leitrim	-	-	-0.101**
	-	-	(0.048)
Longford	-0.147***	-0.177***	-0.178***
	(0.039)	(0.042)	(0.042)
Louth	-	-	-0.040*
	-	-	(0.028)
Mayo	-	-0.059**	-0.067**
	-	(0.024)	(0.024)
Meath	-	-	-0.040*
	-	-	(0.023)
Offaly	-	-0.050*	-0.056*
	-	(0.03)	(0.031)
Sligo	-0.069**	-0.104***	-0.123***
	(0.033)	(0.033)	(0.033)
Tipperary	0.064***	-	-
	(0.025)	-	-
Westmeath	-	-	-
	-	-	-
Wexford	0.068***	-0.039*	-0.051**
	(0.023)	(0.021)	(0.021)
Observations	14,737	17,738	17,552
Pseudo R^2	0.1274	0.1150	0.1209

Note: Standard errors in parentheses.
* significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.
\- designates insignificant.

Table C2: Marginal Effects for Binary Probit Models of Female Claimants' Leaving the Live Register

Variables	Six Month	Twelve Month	Fifteen Month
Personal and Family Characteristics:			
Age Reference Category: Aged 18-24 years			
Aged 25-34 Years	-0.006	-0.034**	-0.031**
	(0.016)	(0.016)	(0.015)
Aged 35-44 Years	-0.054	-0.049***	-0.050***
	(0.019)	(0.018)	(0.018)
Aged 45-54 Years	-0.005	0.013	0.001
	(0.021)	(0.019)	(0.019)
Aged 55+ Years	-0.093	-0.069***	-0.081***
	(0.022)	(0.022)	(0.022)
Health Reference Category: Bad/Very Bad Health			
Very Good Health	0.226	0.332***	0.338***
	(0.051)	(0.047)	(0.045)
Good Health	0.163	0.253***	0.246***
	(0.056)	(0.042)	(0.030)
Fair Health	0.044	0.153***	0.137***
	(0.061)	(0.047)	(0.040)
Marital Status Reference Category: Single			
Married	-0.089	-0.072***	-0.068***
	(0.018)	(0.017)	(0.017)
Cohabits	0.044	-0.000	-0.016
	(0.044)	(0.037)	(0.037)
Separated/Divorced	-0.114	-0.083***	-0.072***
	(0.032)	(0.032)	(0.032)
Widowed	-0.074	-0.057	-0.068
	(0.043)	(0.041)	(0.041)
Children	-0.062	-0.060***	-0.061***
	(0.012)	(0.010)	(0.010)
Spousal Earnings Reference Category: None			
Spouse Earnings €250	0.008	0.014	0.015
	(0.029)	(0.025)	(0.024)
Spouse Earnings €251-€350	0.076	-0.032	-0.048
	(0.091)	(0.084)	(0.084)
Spouse Earnings €351+	-0.136	-0.101***	-0.094***
	(0.017)	(0.017)	(0.017)
Human Capital Characteristics:			
Education Reference Category: Primary or Less			
Junior Certificate	0.001	0.004	0.009
	(0.022)	(0.018)	(0.018)
Leaving Certificate	0.049	0.034*	0.038**
	(0.021)	(0.018)	(0.017)
Third-level	0.131	0.125***	0.124***
	(0.022)	(0.018)	(0.017)
Apprenticeship	-0.011	-0.015	-0.011
	(0.019)	(0.018)	(0.017)

Table C2: Marginal Effects for Binary Probit Models of Female Claimants' Leaving the Live Register (Continued)

Variables	**Six Month**	**Twelve Month**	**Fifteen Month**
Literacy/Numeracy Problems	-0.054	-0.061**	-0.049**
	(0.028)	(0.025)	(0.025)
English Proficiency	-0.006	0.001	0.005
	(0.035)	(0.032)	(0.030)
Employment/Unemployment/Benefit History:			
Employment History Reference Category: Never Employed			
Still In Employment	0.235	0.244***	0.227***
	(0.041)	(0.027)	(0.025)
Employed in Last Month	0.190	0.161***	0.150***
	(0.038)	(0.033)	(0.032)
Employed in Last Year	0.117	0.062*	0.058*
	(0.040)	(0.033)	(0.032)
Employed in Last 5 Years	0.043	-0.029	-0.029
	(0.042)	(0.037)	(0.036)
Employed over 6 Years Ago	-0.030	-0.136***	-0.132***
	(0.057)	(0.051)	(0.050)
Casually Employed	-0.158	-0.160***	-0.154***
	(0.014)	(0.015)	(0.015)
Would Move for a Job	0.080	0.082***	0.077***
	(0.012)	(0.011)	(0.011)
Job Duration Reference Category: Never Employed			
Job Duration Less than Month	-0.002	0.021	0.036
	(0.040)	(0.034)	(0.032)
Job Duration 1-6 Months	0.039	0.069**	0.073**
	(0.036)	(0.030)	(0.029)
Job Duration 6-12 Months	0.070	0.040	0.048
	(0.037)	(0.031)	(0.030)
Job Duration 1-2 Years	0.031	0.041	0.036
	(0.037)	(0.031)	(0.030)
Job Duration 2+ Years	0.000	0.020	0.028
	(0.035)	(0.031)	(0.029)
UE Claim Previous 5 years	0.095	0.126***	0.118***
	(0.011)	(0.010)	(0.010)
Signing for 12 months+	-0.155	-0.188***	-0.166***
	(0.015)	(0.016)	(0.016)
CE Scheme Previous 5 years	-0.036	-0.074**	-0.080**
	(0.040)	(0.037)	(0.037)
On CE Scheme for 12 months+	-0.165	-0.145***	-0.120***
	(0.040)	(0.044)	(0.044)

Table C2: Marginal Effects for Binary Probit Models of Female Claimants' Leaving the Live Register (Continued)

Variables	Six Month	Twelve Month	Fifteen Month
Social Welfare Payment Type Reference Category: UE Credits			
Jobseeker's Allowance	-0.114	-0.115***	-0.113***
	(0.027)	(0.026)	(0.025)
Jobseeker's Benefit	0.096	0.093***	0.087***
	(0.026)	(0.024)	(0.024)
Number of Claims	-0.574	-0.332***	-0.325***
	(0.066)	(0.037)	(0.035)
Location Characteristics:			
Location Reference Category: Rural			
Village	-0.052	-0.024**	-0.030**
	(0.016)	(0.016)	(0.015)
Town	-0.026	0.006	0.002
	(0.016)	(0.015)	(0.015)
City	-0.020	0.003	0.001
	(0.017)	(0.015)	(0.015)
Own Transport	0.030	0.015	0.019*
	(0.012)	(0.011)	(0.011)
Near Public Transport	-0.015	-0.030**	-0.025**
	(0.014)	(0.012)	(0.012)
County Location Reference Category: Dublin			
Carlow	-0.082*	-	-
	(0.044)	-	-
Cavan	-0.137	-0.165***	-0.170***
	(0.036)	(0.038)	(0.039)
Cork	-0.077	-0.038**	-0.041**
	(0.023)	(0.019)	(0.018)
Donegal	-	-0.054**	-0.050**
	-	(0.023)	(0.023)
Galway	-	-	-
	-	-	-
Leitrim	-	-0.110*	-0.118**
	-	(0.060)	(0.060)
Longford	-0.110*	-0.160***	-0.173***
	(0.053)	(0.055)	(0.056)
Louth	-	-0.049*	-0.050*
	-	(0.029)	(0.028)
Mayo	-	-	-
	-	-	-
Meath	-0.060*	-0.062**	-0.063**
	(0.033)	(0.031)	(0.031)

Table C2: Marginal Effects for Binary Probit Models of Female Claimants' Leaving the Live Register (Continued)

Variables	Six Month	Twelve Month	Fifteen Month
County Location Reference Category: Dublin			
Offaly	-0.067*	-0.138***	-0.130***
	(0.038)	(0.039)	(0.040)
Sligo	-0.086*	-0.114***	-0.130***
	(0.042)	(0.044)	(0.044)
Tipperary	0.073**	-	-
	(0.029)	-	-
Westmeath	-0.079**	-0.052*	-0.057*
	(0.032)	(0.030)	(0.030)
Wexford	-	-0.071***	-0.065***
	-	(0.024)	(0.024)
Observations	10,855	13,024	12,915
Pseudo R^2	0.1449	0.1394	0.1389

Note: Standard errors in parentheses.
* significant at 10 per cent; ** significant at 5 per cent; *** significant at 1 per cent.

Appendix D: Distribution of Predicted Welfare Dependence Probabilities for Six and Fifteen Month Profiling Models

Figure D1: Six Month Model: Distribution of Male Welfare Dependence Probabilities

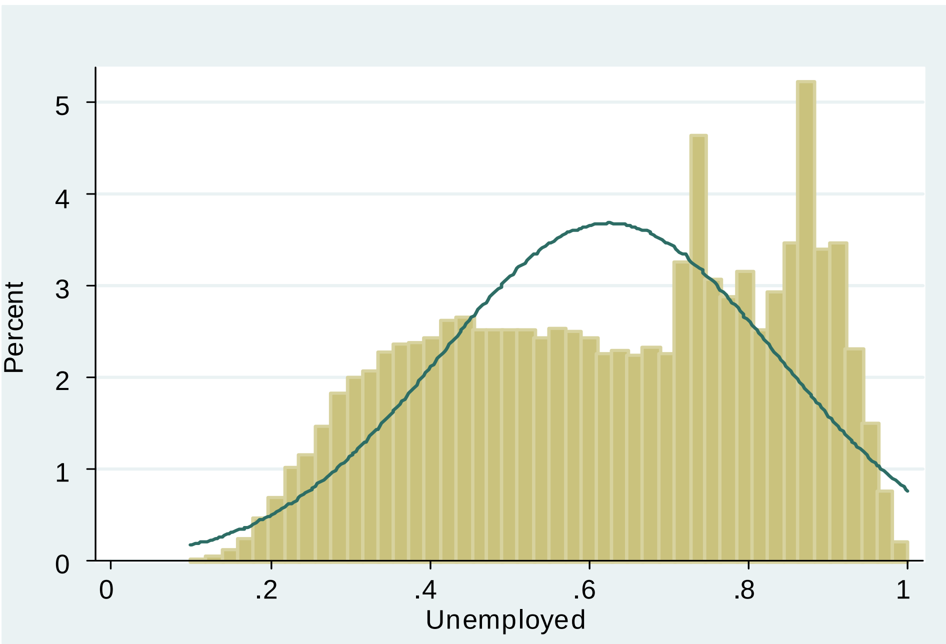


Figure D2: Six Month Model: Distribution of Female Welfare Dependence Probabilities

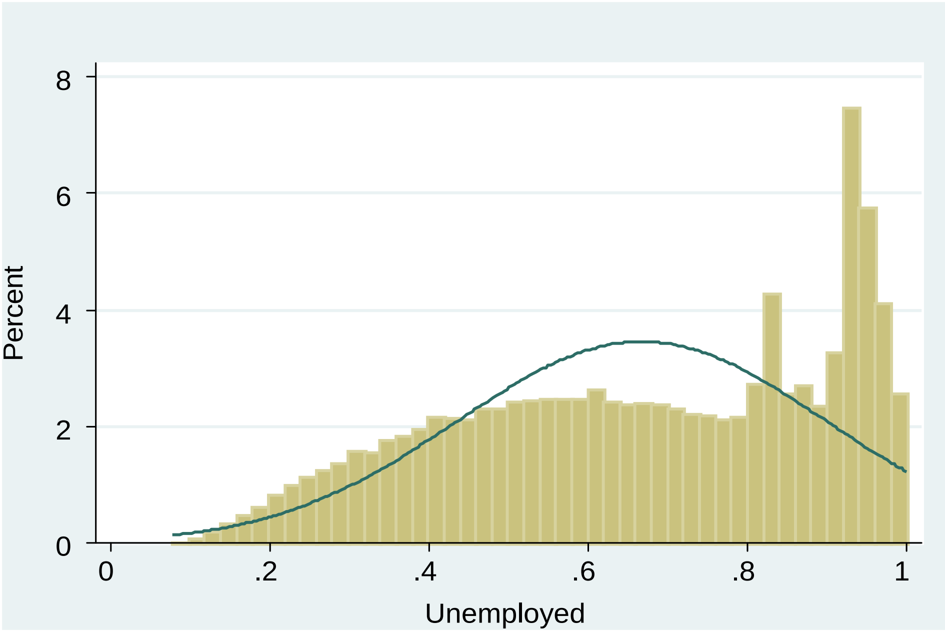


Figure D3: Fifteen Month Model: Distribution of Male Welfare Dependence Probabilities

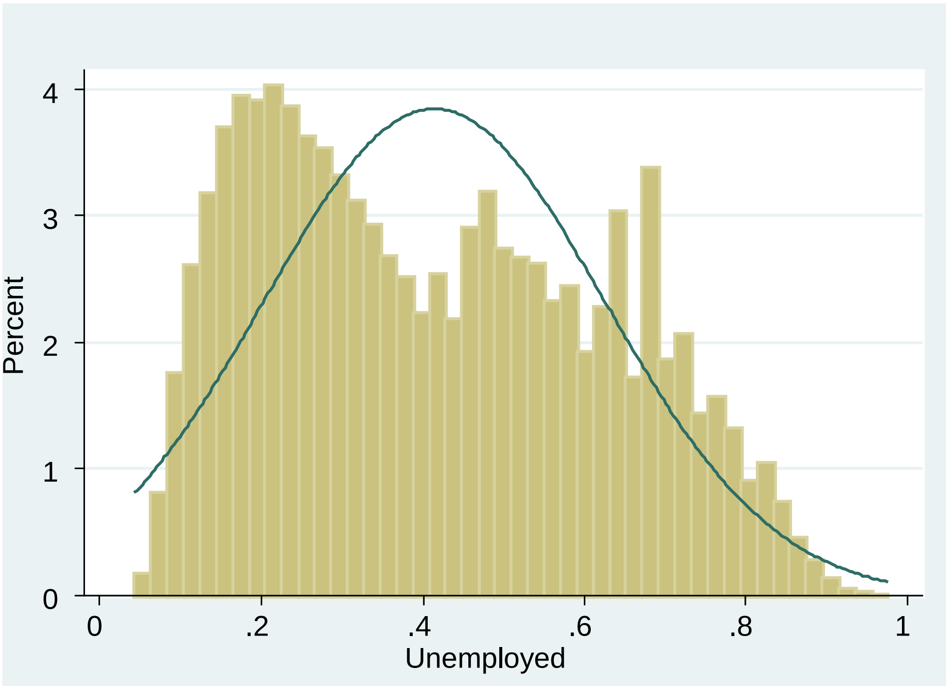


Figure D4: Fifteen Month Model: Distribution of Female Welfare Dependence Probabilities