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A Statistical Profiling Model of Long-Term Unemployment Risk in Ireland

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Abstract: This paper develops a statistical profiling model of long-term unemployment risk in Ireland using a combination of administrative data and information gathered from a unique questionnaire that was issued to all jobseekers making a social welfare claim between September and December 2006 who were then tracked for eighteen months. We find that factors such as a recent history of long-term unemployment, advanced age, number of children, relatively low levels of education, literacy/numeracy problems, location in urban areas, lack of personal transport, low rates of recent labour market engagement, spousal earnings and geographic location all significantly impact the likelihood of remaining unemployed for 12 months or more. While the predicted probability distribution for males was found to be relatively normal, the female distribution was bimodal, indicating that larger proportions of females were at risk of falling into long-term unemployment. We find evidence that community based employment schemes for combating long-term unemployment have little effect as participants re-entering the register typically experience extended durations. Finally, we argue that the adoption of an unemployment profiling system will result in both equity and efficiency gains to Public Employment Services.

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I Introduction

In most industrialised economies, expenditure on Public Employment Services (PES) to jobseekers to assist them to reintegrate into the labour market constitute a large proportion of governments' welfare budgets. In order to ensure that these scarce resources are targeted towards individuals that are most in need of them, particularly those in danger of falling into long-term unemployment, a number of countries have developed and implemented statistical profiling[1]. This is a tool whereby a numerical score, calculated on the basis of multivariate regression, determines the referral of an unemployed person to various interventions (e.g. active labour market programmes) designed to enhance their chances of securing employment. The estimated score ranks each jobseeker in terms of their risk of becoming long-term unemployed and PES staff can then use this measure to identify those who are most in need of assistance. Overall, the main objective in using statistical profiling is to deliver intensive services early, to those most in need of them, rather than after long-term unemployment has occurred.

This paper assesses the potential for the development of a profiling model in Ireland. The study is based on a unique combination of administrative data from Ireland's Live Register database, along with survey data from a unique questionnaire that was administered to all individuals who made a claim for unemployment benefit over a thirteen week period between September and December 2006[2]. Those that made a claim during this time period were subsequently tracked over the following 78 weeks (i.e. eighteen months) by the Department of Social and Family Affairs (DSFA)[3] administrative IT system[4]. This tracking enabled us to develop six, twelve and fifteen-

[1] Examination of the use of statistical profiling began in the 1980s, when there was a significant growth in long-term unemployment in many OECD countries. This issue led governments to realise that it would be too costly to provide PES to all jobseekers and that they needed some type of mechanism to identify and target their scare resources to those most at risk of long-term unemployment.
[2] Republic of Ireland only.
[3] Government department that administers unemployment and other types of social welfare payments in Ireland.
[4] The Integrated Short-Term Scheme (ISTS) i.e. the Live Register database.

month profiling models. In this paper, we primarily focus on the twelve-month profiling model; however, a brief discussion of the results produced by the other two models is presented in Section VI.

The central objective in developing a profiling model is that it allows us to assess the factors influencing an individuals' unemployment spell. Furthermore, the model potentially provides policy-makers with a framework that will enable them to estimate, at the time a claim is made, an individual's likelihood of remaining on the Live Register after six, twelve or fifteen months. Policy-makers can then use the measure that is produced by the profiling model to identify jobseekers that require immediate reemployment services. Thus, the study provides insights both from the perspective of developing a profiling system and the wider mechanisms determining LT unemployment.

The potential introduction of a profiling system in Ireland represents a stark contrast to that currently operated under the National Employment Action Plan (NEAP) whereby all individuals are referred for reemployment assistance to FÁS, the national employment and training agency, after a three-month unemployment spell has elapsed. This existing blanket approach to assisting unemployed individuals is potentially inefficient on a number of fronts. Firstly, under the current three-month rule, many jobseekers who would have found employment on their own before, say, a twelve-month point, will receive support after passing the three-month NEAP threshold. Such interventions will ultimately prove unnecessary, thereby representing a waste of government resources. Secondly, early interventions for the chronically disadvantaged 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 for those most with a high risk of long term unemployment.

The remainder of the paper is structured as follows. In Section II we provide a more detailed description of profiling as a policy instrument. This is followed in Section III with an overview of other countries experiences with profiling. Data and methodological issues are outlined in Section IV. This is followed in Section V by a descriptive examination of the data. The results from our statistical profiling model are presented in Section VI. Finally, we conclude in Section VII with a summary of our findings.

II Profiling as an Intervention Mechanism

There are a number of alternative approaches to the largely indiscriminate unemployment intervention mechanism that is currently adopted in Ireland. These alternative approaches include ‘eligibility rules’, ‘caseworker discretion’, ‘screening’ and ‘profiling’ (Hasluck, 2008). The *eligibility rule’* approach describes a process whereby individuals are channelled towards various forms of reemployment support on the basis of meeting certain criteria. *Caseworker discretion* is where PES staff use their 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 *screening* describes the process whereby the caseworker attempts to score the jobseeker’s employability, typically using psychologically-based techniques. As indicated previously, *statistical profiling* is a method of assessment where the claimant’s suitability for reemployment support is based on a probability of becoming long-term unemployed, which is generated by a formal statistical model that uses a range of characteristics of the individuals concerned (e.g. age, education level, unemployment history, etc.)

In this study, we focus on statistical profiling as an intervention approach because of its potential predictive accuracy. Furthermore, profiling’s fundamentally objective nature makes it a potentially superior method of assessment compared to the other largely subjective approaches mentioned. There are, however, some potential drawbacks to the system. First, there is the possibility that poorly performing models may incorrectly identify individuals for intervention i.e. deadweight[5]. Second, 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. Third, the initial set up costs may be quite substantial. Despite these potential drawbacks, profiling offers a number of potential advantages and the development of a successful statistical profiling should generate a more efficient and effective intervention system in Ireland compared to the current blanket approach of

[5] This describes the situation whereby an individual incorrectly identified, through any type of intervention mechanism, is sent for reemployment assistance.

targeting all jobseekers after three months. This is because profiling can provide a basis for targeting and therefore lead to a reduction in the aggregate number of interventions. In addition, provided such interventions are successful, the incidence of long-term unemployment should also be reduced. Furthermore, with a profiling system the intensity of interventions can be varied according to the risk of long-term unemployment. Also, a profiling score provides the caseworker with more detailed information on the challenges facing each individual claimant, which allows for a more tailored approach to support. Finally, given that profiling generates an implicit ranking system, based on a jobseeker's estimated probability of exiting unemployment, the numbers receiving interventions can be adjusted in line with PES resources and places can be allocated on the basis of objectively determined need.

The general concept of statistical profiling is illustrated by the *Long-Term Unemployment Risk Barometer* depicted in Figure 1[6]. Depending on their particular circumstances, each individual making a claim for unemployment benefit will have a risk of becoming long-term unemployed ranging from 1 to 100 per cent. Having estimated this, policy-makers can then choose a cut-off point, which will depend on both departmental objectives and resources, above which all individuals will be directed towards reemployment services.

< Insert Figure 1 Here >

III Other Countries' Experiences of Statistical Profiling

During the 1990s, a number of countries experimented with statistical profiling models and two of them - the United States (US) 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, including, the Netherlands, New Zealand and South Korea. However, none of these countries have implemented systems on the same scale as the US, Australia, Denmark or Germany. In addition to Ireland,

[6] 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.

countries currently testing profiling models include Bulgaria, France, Hungary, Mexico, Slovakia and Sweden, (Hasluck, 2008; Arnkil *et al*., 2006; 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 experimented with a profiling model[7] but decided not to implement it as a practical instrument following concerns about the model's accuracy (Gibbins, 1997; Wells, 1998)[8]. However, a study by Bryson and Kasparova in 2003 concluded that it would be beneficial to use profiling to predict the benefit spells of Jobseeker's Allowance (JSA) claimants, lone parent and disabled people on benefit[9]. Following Bryson and Kasparova's (2003) findings, the UK PES implemented a profiling system for jobseekers on incapacity benefit (Behncke *et al*., 2007)[10].

A mandatory Worker Profiling and Re-employment Services (WPRS) system has been in operation in each state in the US since 1993. 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 unemployment insurance benefits[11]. The prediction, or score, comes from an econometric model. Due to civil rights concerns, age, gender and race/ethnic group variables cannot be included in the state model, which tends to compromise the predictive power of the model. Consequently, the main covariates used tend to be restricted to educational attainment, job tenure, previous occupation and previous industry. Some states, however, include many additional variables[12]. In all states, profiled claimants are allocated to mandatory reemployment services according to their computed risk score and caseworker discretion is explicitly prohibited with these programmes (Frölich *et*

[7] The Department of Work and Pensions and JobCentre Plus, the UK PES.
[8] See also Hasluck (2008).
[9] Bryson and Kasparova (2003) argued that profiling represented a more accurate system of identification compared to random allocation.
[10] 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.
[11] In order to keep deadweight to a minimum, a process is used to select UI claimants to profile (OECD, 1999).
[12] See Black *et al*. (2003) for the various variables that different states include in their profiling models.

al., 2003; Bimrose *et al.*, 2007). However, caseworkers can decide on the assignment of other types of non-mandatory services (Lechner and Smith, 2007)[13].

Australia's experience with statistical profiling dates back to 1994. The current Job Seeker Classification Instrument (JSCI) has been in use since 1998 and is used primarily for the identification at registration of those with the greatest risk of long-term unemployment. A logistic regression model estimates the relative weight or 'points' of 18[14] risk factors (i.e. variables) that have been identified by Australian policy-makers as being associated with long-term unemployment[15]. Following the profiling exercise, based on an individual score, caseworkers then decide on the most appropriate form of reemployment support.

In 2004, a profiling system became an integrated part of the Danish national labour market policy. A duration model is used to estimate the probability that an individual will still be unemployed in six months time conditional on the elapsed duration of unemployment. A wide range of explanatory variables are incorporated into the model, including age, residence, marital status, health, immigrant status, unemployment history, etc.[16]. The statistical model is estimated using 120 subgroups, stratified according to age, gender, benefit eligibility and region of residence. The model outputs are used by caseworkers to allocate the claimant to a service that meets his/her needs.

[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] The JSCI statistical model was reviewed and updated in 2003, 2006 and again in 2008. The assessments that took place resulted in some new risk factors being included in the model and others being removed. Access to transport, proximity to labour markets (non-survey factor), duration of unemployment and small community dynamics were factors that were omitted after the 2003 review but the first two of these were reintroduced after the 2008 review. A new risk factor - income support history - was also included after the 2008 assessment. A factor to capture the additional disadvantage for Indigenous jobseekers in rural and remote communities was also introduced after the 2006 review. Re-weighting of the risk factors was undertaken on all occasions (see Lipp, 2005; and DEEWR, 2009).

[15] Age, gender, educational attainment, language and literacy, recency of work experience, location, disability/medical condition, family status and contactability, along with certain personal characteristics (e.g. poor presentation) that require some judgement to be made by the caseworker are examples of some of the rick factors used.

[16] Educational attainment, previous wage and working experience are not in the dataset used. However, the Danish labour market authority is planning to gather this type of information in the register so that it can be used in their profiling model.

Statistical profiling was introduced in Germany in 2005. The system utilised a binary probit model incorporating personal characteristics and labour market information. Based on their probability score, claimants are then classified into one of four categories and assigned to tailor-made action programmes (Bimrose *et al*., 2007).

In terms of the effectiveness of the profiling systems that have been implemented, the evidence that is available demonstrates that it is possible to generate accurate models from a statistical standpoint. (Wandner, 1998; Lipp, 2005; Fahr and Sunde, 2006; Rosholm *et al*., 2006; Hasluck, 2008) Nevertheless, it is important to stress that the primary role of profiling is to channel individuals towards the most appropriate form of Active Labour Market Programme (ALMP); thus, profiling will have little impact unless accompanied by an effective range of ALMPs.

IV Data and Methodology

Data

The data collection process for this study was quite unique. In order to build on the limited administrative information available from the Live Register[17], a specially devised questionnaire was administered to all individuals registering an unemployment claim in the Republic of Ireland during a 13 week period, running from September to December 2006. The information collected included educational attainment, literacy/numeracy levels, health, access to transport, employment/unemployment/job history, and participation on public job schemes, such as the Community Employment (CE) scheme.[18] Those profiled were subsequently tracked for a further 78 weeks[19].

The total number of records contained within the initial population database was 60,189 (Table 1). After the elimination of duplicate records and individuals who had registered for benefits other than Jobseekers Allowance (JA) or Jobseekers Benefit

[17] Only data on marital status, spousal earnings and location were obtained from the Live Register.
[18] The CE scheme is operated by FÁS and it is designed to help people 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.
[19] Given that the initial profiling took place over a 13 week period, the total follow up periods are 39 weeks (26+13) in respect of the six-month model, 65 weeks in respect of the twelve-month model, and 78 weeks in respect of the fifteen-month model.

(JB), the population fell to 57,492. Of these 44,732 individuals had their claims awarded and, as such, these individuals represent our target population of unemployed claimants. The survey questionnaire was successfully administered to 33,754 individuals giving us a response rate of just over 75 per cent.

< Insert Table 1 Here >

Our profiling models distinguish between 'stayers' on the Live Register and 'leavers' who achieved a sustained exit to employment. When constructing the twelve-month profiling model, we consider the status of individuals at week 65 in the data[20]. We initially define leavers as individuals who had their claim closed and, consequently, had left the Live Register to employment at some point prior to 65 weeks and did not have a subsequent JA or JB unemployment application activated. Given this initial categorisation, almost 60 per cent of the sample was estimated to have exited the Live Register at the end of the 65 week period. However, not all of this leaver sample, as it is currently defined, would have exited to the labour market, nor would all of the identified stayers (41 per cent) 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, we made appropriate adjustments to our originally defined leaver and stayer samples before building our twelve-month profiling model. In particular, we made three adjustments to the leavers' sample. First, individuals whose JA or JB claims were closed at the end of the 65 week period, but, who moved across to alternative benefits, were redefined as stayers (2,377) on the grounds that administrative differences between unemployment and other, non-unemployment, welfare statuses are largely irrelevant, and impossible to predict, in an exercise such as this. Second, individuals who had exited the register by week 65 who had nevertheless accumulated 52 weeks or more of unemployment duration were redefined as stayers having met the criteria for LT unemployment (390). Finally, leavers whose reason for closure was unknown were eliminated from the sample (2,361) as it was impossible to establish the extent to which such individuals were genuine exits to employment as opposed to administrative closures. In relation to the

[20] 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.

stayers' sample, any claimant who had exited the Live Register for a substantial period during the 65 week observation period[21] was redefined as a leaver. This adjustment resulted in a total of 4,031 stayers being redefined as leavers. Individuals exiting for a sustained period whose reason for closure was unknown were dropped from the stayers' sample (631). Consequently, the final sample used to construct our twelve-month profiling model consisted of 30,762 individuals, of whom 18,756 (61 per cent) were leavers at 65 weeks and 12,006 (39 per cent) stayers (see Table 2)[22].

< Insert Table 2 Here >

We noted that about 11,000 individuals, whose unemployment compensation claims were approved, were not administered the profiling questionnaire. This group, 25 per cent of the population of successful claimants during the initial data collection, is analogous to non-respondents to a survey, and it is important to ensure that these individuals do not differ significantly, in terms of their characteristics, from the profiled population. Checks on the respondent and non-respondent samples, using some broad characteristic information available in the Live Register database, revealed that in terms of gender, age and marital status, both samples are virtually identical (see Table 3). However, a slightly a higher proportion of non-respondents were non-Irish: (87.7 per cent of those profiled were Irish nationals, compared to 85.6 per cent of non-respondents), suggesting that this sub-group contained a larger number of individuals that are likely to have been 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 unemployment benefit claimant population.

< Insert Table 3 Here >

Having applied our various restrictions and exclusions, Figure 2 plots the Kaplan-Meier (KM) survivor function, which calculates the fraction of individuals leaving the

[21] Here we define a substantial period as greater than six weeks (before re-entering the Live Register at a later period).
[22] Additional information on the leaver and stayer sample adjustments is available from the authors on request.

Live Register to enter the labour market during successive weeks. The chart suggests that our data management strategies generate sensible results, given that the rate of exit from unemployment appears relatively constant up until around week 40 at which point the curve begins to flatten somewhat. After week 55 the exit rate becomes lower again, which indicates that the likelihood of a successful labour market exit from week 55 onwards declines substantially.

< Insert Figure 2 Here >

Methodology

In developing a profiling model the dependant variable used will be determined by the objectives of the profiling project, a decision that is driven by policy objectives of PES (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 will reflect the risk of remaining unemployed for more than 52 weeks (i.e. twelve months).

Two estimation strategies dominate the profiling literature. The first involves logit or probit models while the second relates to duration. While most countries tend not to disclose information on their modelling approach, the majority of those that have appear to favour the use of a binary variable, including the two countries with the longest experiences of profiling – the United States and Australia[23]. As there is no convincing evidence for the use of one methodological approach over the other, on the basis of common international practise and the difficulty of measuring duration spells from the Live Register, we focus on the binary outcome variable in this study and, therefore, implement a probit model. Furthermore, the probit approach has the added advantage of providing us with a readily available probability score that will be easily interpreted by PES administrators.

[23] 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 (Black *et al.*, 2001).

The following controls are included in our profiling model to predict those at risk of staying on the Live Register for 12 months or more: age; marital status; education; prior 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; previous job duration; willingness to move for a job; previous unemployment claim history; participation in the CE scheme; benefit type; number of claims and spousal earnings. As indicated earlier, information on these covariates came from the questionnaire that was administered to all claimants as well as from the Live Register database.

On the grounds that the impact of different covariates will vary according to gender, for example, family background or the presence of children, we estimate separate models for both males and females.

Section V: Bivariate Analysis

Table 4 reports the average values for stayers and leavers 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 two groups appear to be marginal; however, leavers are slightly more likely to be younger and/or male. In relation to marital status, individuals who are single appear more likely than their married counterparts to exit the Live Register to employment. It is likely 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[24] due to the absence of dependant children. Regarding health, respondents were asked to subjectively rate their current health status and, as might be expected, leavers were found to be in somewhat better health: 95.4 per cent reported a health status of very good/good compared to 88.8 per cent of stayers.

The profiling questionnaire also collected information on the incidence of apprenticeship training and perceived levels of basic numeracy/literacy. While leavers

[24] 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.

were slightly more likely to have served an apprenticeship, 15 per cent compared to 13 per cent, much starker differences were apparent with respect to basic skills. Specifically, the incidence of literacy/numeracy problems among stayers was twice that of leavers, suggesting that a lack of such basic skills could represent a substantial barrier to full labour market participation. Similarly, claimants who were assessed by interviewers (i.e. PES staff) to exhibit 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 substantially more likely to leave the Live Register, which is likely to reflect the ability to search for employment over a greater geographical distance. However, access to public transport does not appear to represent a significant factor in determining the rate of exit from unemployment.

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 level. 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 32 per cent of leavers held Third-level qualifications compared to just 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.

< Insert Table 4 Here >

Section VI: Model Results

Twelve-Month Model

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 describe the impact of each of the covariates on the probability of a claimant leaving the Live Register for employment after 12 months, holding the other factors that are included in the model constant[25].

Turning firstly 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. In particular, those males who had signed on for more than 12 months in the last 5 years were 17 per cent less likely to exit before 52 weeks. In addition, males with previous exposure to the CE scheme had a reduced likelihood of avoiding long-term unemployment. Relative to the omitted category of males who had not made an unemployment claim in the previous 5 years, those that had were somewhat more likely to exit the Live Register. This result seems to be counterintuitive but 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. However, some finer detail on the question relating to the duration of previous unemployment spells would be necessary to confirm this. The finding that the individuals who participated in the CE scheme tended to have extended unemployment durations suggest that the programme is relatively unsuccessful in terms of breaking the pattern of LT unemployment for individuals re-entering the live register. Of course, it could be the case that the primary impact of the CE programme is felt through higher exit rates from the register. However, previous research suggests that this is, in fact, not the case as O'Connell (2002) reports that CE participants were less likely, relative to a control group, to find subsequent employment. Thus, our current finding, when considered in conjunction with previous research, raises further serious questions regarding the effectiveness of the Community Employment Scheme as an active labour market policy.

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, the decline in the probability of exiting the Live Register before week 52 ranged from 3 per cent for those aged 25-34 to 22 per cent for persons aged 55 or over.

[25] In the modelling, we do not use interactions 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.

Some family background characteristics were found to be important predictors of welfare dependency for males as well. For example, while married males were more likely than single males 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 less than €250 per week were more likely to exit to the labour market prior to the twelve month 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 and upper second-level qualifications 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 competencies, males reporting literacy or numeracy problems were 7 per cent less likely to leave the Live Register before 52 weeks. This latter result confirms the view that a lack of basic skills remains a substantial barrier to successful labour market participation.

Having access to ones own transport increased the probability of a successful labour market exit by 6 per cent, while males that expressed a willingness to relocate for employment purposes were 4 per cent more likely to find a job.

Males with more recent labour market attachments, that is those on JB or recently\currently employed, had a higher probability of exiting to employment. Those casually employed, however, were some 9 per cent more likely to remain on the Live Register for twelve months or more, which suggests that employment of this nature may not, in fact, facilitate a successful transition off the Live Register to more stable employment.

Finally, with respect to location, relative to those living in smaller rural areas, males located in cities were 6 per cent more likely to remain on the Lie Register. This result suggests that ready access to large local labour markets is of little advantage in the Irish case. With respect to specific county effects, relative to Dublin exist rates were lower among males located in some more rural counties in Ireland.

The results from the Female profiling model are reported in the second column of Table 5. While the predictors of long-term unemployment are similar to those reported for males, the model differs in a number of important respects. For example, compared to males, the marginal impact of age is much lower for females. In addition, relative to single persons, females who are married or separated/divorced 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. The latter two results largely reflect the greater tendency of females to undertake family responsibilities which, in turn, may reduce their ability or willingness to find employment.

Finally, with respect to county effects, relative to Dublin, exit rates were lower for females living in some of the more rural Irish counties. Moreover, where the marginal effects of counties achieve statistical significance in both male and female models, they are similar in sign and broad order of magnitude[26].

< Insert Table 5 Here >

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 6 and 7 describe the extent to which our twelve-month models successfully predicted male and female leavers and stayers at various probability cut-off points.

If we take males (Table 6) with a predicted probability above 0.5[27] as likely to exit to the labour market before 52 weeks (i.e. a leaver) and those with a predicted 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, with the corresponding figure for leavers standing at 71 per cent. The results from the

[26] The county results for both the male and female models are available from the authors on request.
[27] The cut-off point used for identifying those at risk of falling into long-term unemployment is 0.5, i.e. individuals have a 50:50 chance of staying on the Live Register or leaving it.

female model (Table 7) are very similar, with little difference discernable between the two models in terms of their predictive power.

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, the overall accuracy of the male and female models are 83 and 85 per cent respectively (Tables 6 and 7). At this cut-off point, 81 per cent of males and 87 per cent of females that were classified as stayers on the Live Register 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 at higher cut-off points those individuals identified will be increasingly high risk, in terms of their likelihood of becoming long-term unemployed, and, as a consequence, the likelihood that public resources will be expended on those individuals most in need of assistance increases strongly.

< Insert Table 6 Here >

< Insert Table 7 Here >

Most countries do not release specific details on their profiling model's predictive power, or on the exact specification that lies behind it, so it is difficult to compare our model with those of other countries. 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 models generated here for Ireland. The Danish model is estimated at six months unemployment duration. and, at the 0.5 per cent cut-off point, the Danish model reports a percentage correctly predicted figure of 66 per cent. Our six month models achieve 68 and 69 per cent correct predictions for males and females respectively[28], which is marginally better than its Danish counterpart. Rosholm *et al*. (2006) also found that the Danish

[28] The results for the male six-month profiling model are presented in Table A1 in the appendix, while the results for the female model are available from the authors on request.

male model had a higher predictive power than the female model. 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.

Where Should the Cut-Off Point Be?

Figures 3 and 4 illustrate the distribution of predicted long-term unemployment probabilities among both males and females respectively. The male distribution (Figure 3) appears quite normal, 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 individuals targeted for immediate intervention. However, the female distribution (Figure 4) is much more bimodal in nature, 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 intermediate intervention will ultimately be a matter for policy-makers, which will depend crucially on their objectives and resources. From a policy perspective, the unusual shape of the female distribution is a concern, particularly given the uncertainty surrounding the factors driving the effect. One would suspect that the larger relative impact of dependant children and marital breakup may be moving higher proportions of females towards the upper end of the probability distribution, however, addressing this question falls somewhat outside the scope of the current study.

< Insert Figure 3 Here >

< Insert Figure 4 Here >

Comparison of the Six, Twelve and Fifteen-Month Profiling Models

Tables A1 in the Appendix present the results from our three profiling models – six, twelve and fifteen-month models for males. 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. Similar results were also found in the female models[29].

Table 8 shows the correlations between our six, twelve and fifteen-month profiling models. Both the male and female models are each highly correlated. In relation to the male models, the correlations range from .71 for the six and fifteen-month models to .94 for the twelve and fifteen-month models. Similar correlations emerge between the female profiling models (.73 and .94 respectively). The lower correlations between the six and twelve (fifteen) month models suggest that there is some movement off of the Live Register during these time points. However, the higher correlations that emerge between the twelve and fifteen month models indicate that there are considerably less exits to employment between twelve and fifteen months; thus, those individuals that are on the Live Register after twelve months are still likely to be unemployed after fifteen months.

Section VII: Summary and Conclusions

This paper outlines the results of an Irish profiling model using data that tracks the progress of unemployment benefit claimants over an eighteen month period 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 from September to December 2006.

The statistical profiling models, for both males and females, which were estimated from this data, are well specified. The results from the male model indicate that the probability of remaining on the Live Register for 52 weeks or more is associated with increasing age, number of children, relatively low education, literacy/numeracy problems, location in urban areas, lack of personal transport, recent unemployment and geographic location. We find that individuals who previously participated in community employment schemes aimed at getting long-term claimants back to work

[29] Results available from the authors on request.

have a higher likelihood of returning to long-term unemployment. This finding, when considered in conjunction with the findings of previous research (O'Connell (2002), Denny et al (2000)) raises serious questions with respect to the effectiveness of this particular form of labour market activation. The results from the female model are broadly similar to those of males. However, some differences were apparent in the areas of spousal income, the impact of children, education and location. We find that the female predicted probability distribution is distinctly bimodal in nature, suggesting that these differential impacts may be significant in propelling larger proportions of females towards a much higher probability of long-term unemployment.

In terms of predictive power, the Irish profiling model was found to outperform the profiling model that has been implemented in Denmark. Unfortunately, none of the other countries whose profiling models were examined release specific details on their model's predictive power.

In conclusion, it is our view that there is much to be gained from statistical profiling, both in terms of efficiency and equity, relative to the generally non-discriminatory intervention approach that currently operates in Ireland. Furthermore, the empirical evidence suggests that the data will support the development of a profiling system that compares well with those currently implemented in other countries.

It should, however, be acknowledged that even the most accurate profiling model is only as good as the labour market interventions with which it is associated. Fully exploiting the potential of profiling also requires the development and delivery of effective active labour market programmes, and further research is necessary to establish the effectiveness of programmes currently implemented in Ireland.

Tables

Table 1: Sample Information

Profiling Data	**Numbers**
Original Population	60,189
Exclusions:	
- Duplicates	*1,164*
- Non JA and JB Claims	*1,533*
	57,492
Awarded JA and JB Claims	44,732
Questionnaire Information	33,754
- Leavers at 12 Months	*19,853(59%)*
- Stayers at 12 Months	*13,901 (41%)*

Source: DSFA Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

Table 2: 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 52-Plus 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: DSFA Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire

Table 3: Comparison of Questionnaire Respondents and Non-Respondents

	Respondents (%)	Non-Respondents (%)
Characteristics:		
Male	57.3	57.5
Married	35.0	35.7
Age	36.5	37.2
Irish National	87.7	85.6

Source: DSFA Integrated Short-Term Scheme (ISTS)

Table 4: Key Characteristic Information on the Stayers and Leavers

	Stayers (%)	Leavers (%)
Age	37.7	35.7
Gender:		
Male	57.2	57.9
Female	42.8	42.1
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
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
Apprenticeship	12.6	14.9
Literacy/Numeric Problems	9.7	4.6
English Proficiency	3.3	2.5
Own Transport	55.6	63.2
Public Transport	73.2	72.3
Educational Attainment:		
Primary or Less	17.1	9.4
Junior Certificate	30.7	24.5
Leaving Certificate	31.8	33.8
Third-level	19.6	31.7

Source: DSFA Integrated Short-Term Scheme (ISTS) and Profiling Questionnaire.

Table 5: Marginal Effects for Binary Probit Models of Male and Female Claimants Leaving the Live Register to Employment

Variable	Males	Females
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)
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)
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)
English Language Proficiency	-0.034	0.001
	(0.023)	(0.032)
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)

Table 5: continued

Variable	Males	Females
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)
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)
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)
Would Move for a Job	0.038***	0.082***
	(0.008)	(0.011)
UE Claim Previous 5yrs	0.044***	0.126***
	(0.009)	(0.010)
Signing for 12mths+	-0.166***	-0.188***
	(0.012)	(0.016)
CES Previous 5yrs	-0.070***	-0.074**
	(0.027)	(0.037)
On CES for 12mths+	-0.071**	-0.145***
	(0.035)	(0.044)

Table 5: continued

Variable	Males	Females
Social Welfare Payment Type Reference Category: Unemployment Credits		
Jobseeker's Assistance	0.014	-0.115***
	(0.028)	(0.026)
Jobseeker's Benefit	0.194***	0.093***
	(0.027)	(0.024)
Number of Claims	-0.085	-0.332***
	(0.053)	(0.037)
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)
Observations	17,738	13,024
Pseudo R^2	0.1150	0.1394

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

Table 6: Reliability Tests: Male Twelve-Month Model

	50% Cut-off	60% Cut-off	70% Cut-off	80% Cut-off
Correctly Predicted:				
	12,282	9,739	6,488	2,780
	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

Table 7: Reliability Tests: Female Twelve-Month Model

	50% Cut-off	60% Cut-off	70% Cut-off	80% Cut-off
Correctly Predicted:				
	9,088	7,299	5,062	2,516
	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

Table 8: Six, Twelve and Fifteen-Month Profiling Model Correlations

	Six-Month	Twelve-Month	Fifteen-Month
Male Profiling Models:			
Six-Month	1		
Twelve-Month	0.7593	1	
Fifteen-Month	0.7144	0.9409	1
Female Profiling Models:			
Six-Month	1		
Twelve-Month	0.7762	1	
Fifteen-Month	0.7314	0.9423	1

Figures

Figure 1: Profiling "Long-Term Unemployment Risk Barometer"

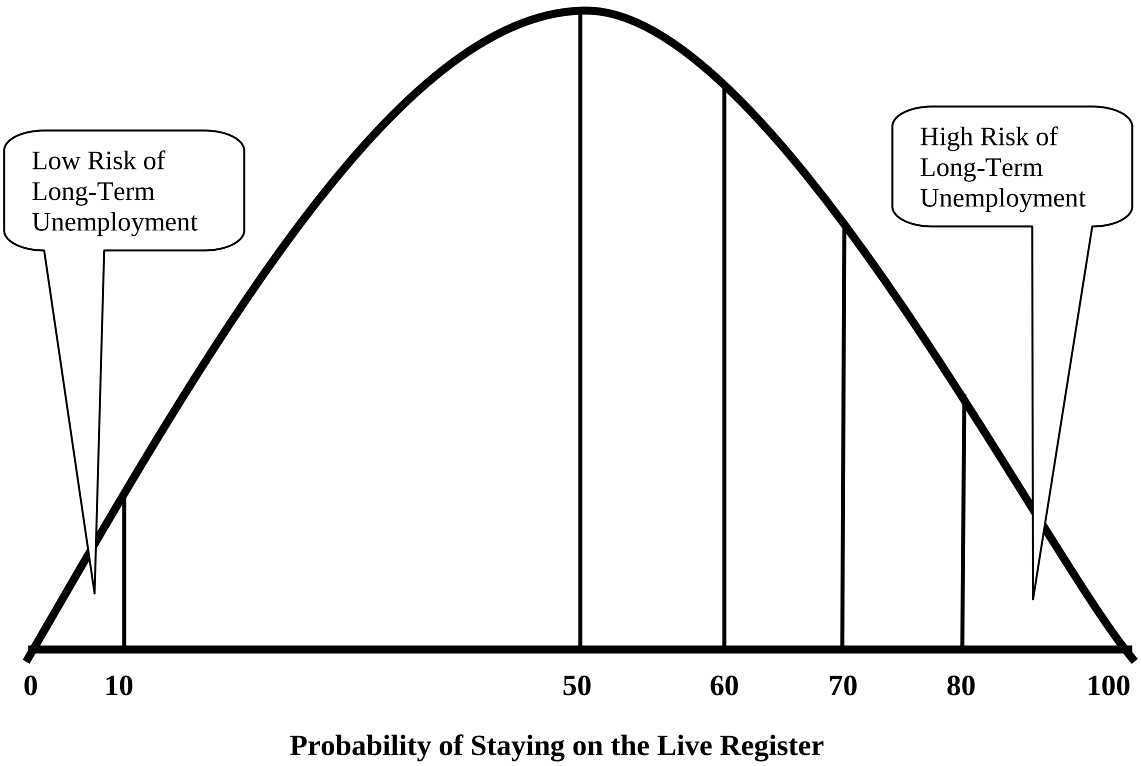


Figure 2: Kaplan-Meier Survival Function: Exits to the Labour Market

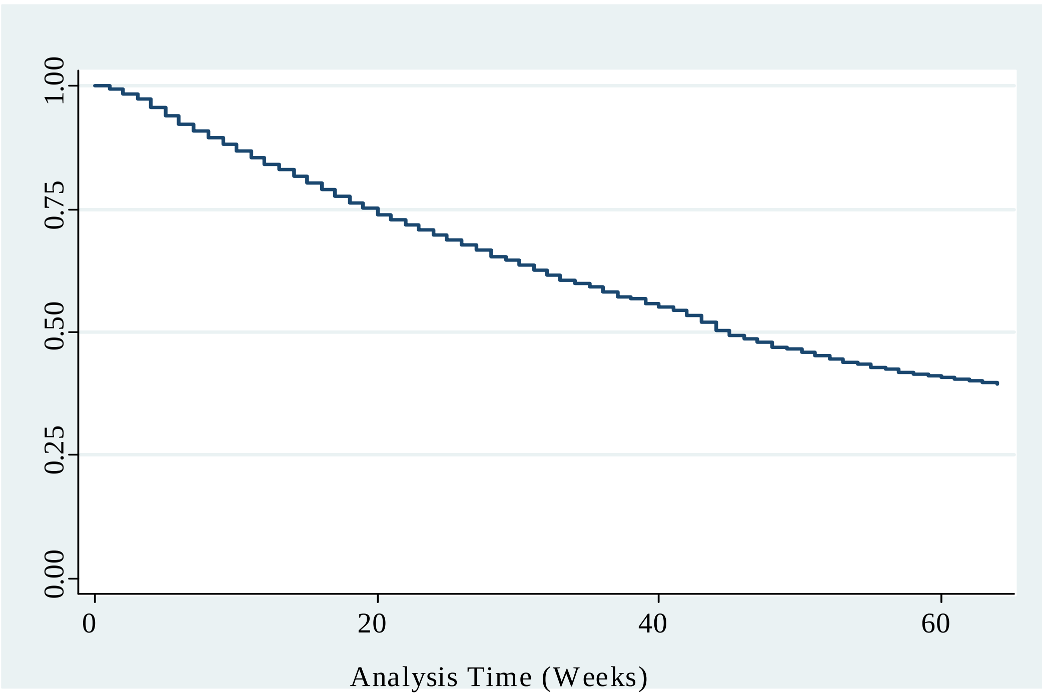


Figure 3: Distribution of Male Welfare Dependence Probabilities

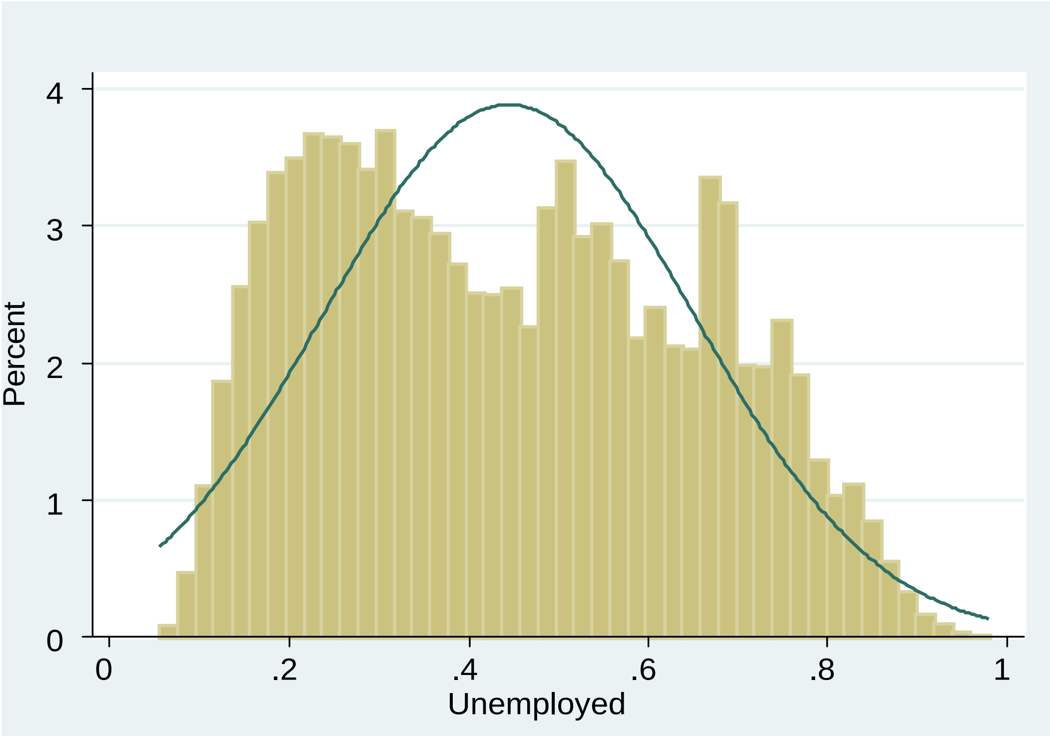
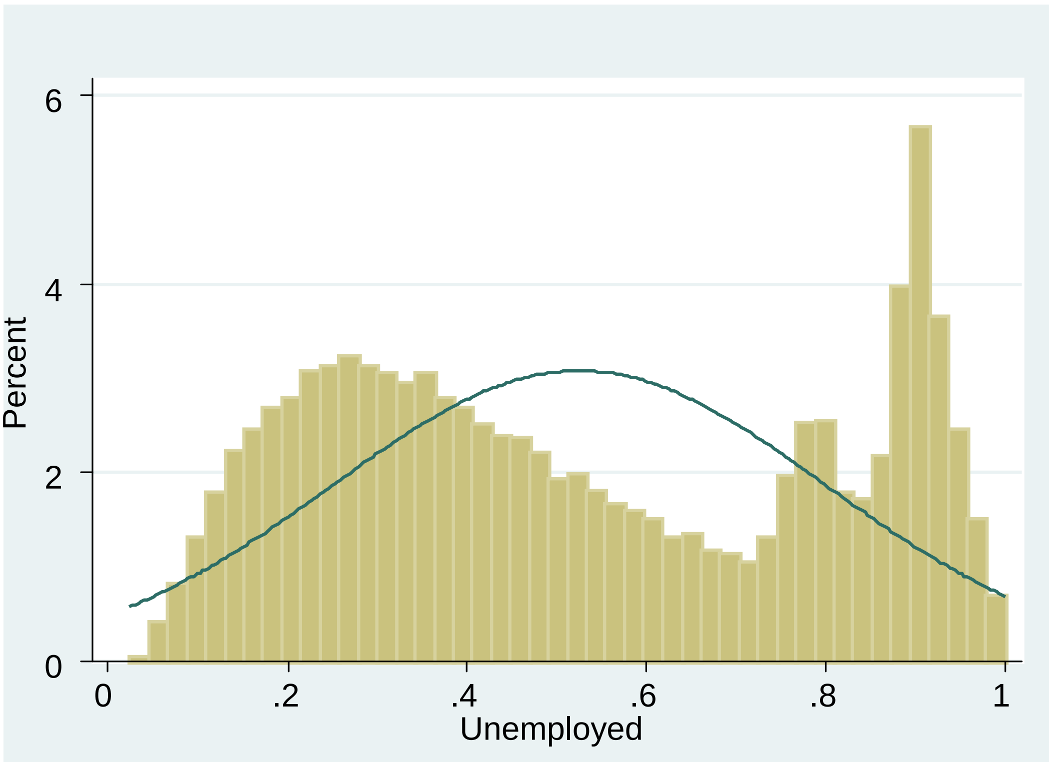


Figure 4: Distribution of Female Welfare Dependence Probabilities



References

Arnkil, R., G. Di Domenico & R. Konle-Seidl. (2008). Joblessness as a Major Challenge for Public Employment Services: Country Reports from Germany, Italy and Finland. In Blanpain, R. & M. Tiraboschi (eds.), *The Global Labour Market: From Globalisation to Flexicurity*, The Netherlands: Kluwer Law International.

Behncke, S., M. Frölich & M. Lechner. (2007). *Targeting Labour Market Programmes: Results from a Randomized Experiment*. IZA Discussion Paper 3085.

Behncke, S., M. Frölich & M. Lechner. (2006). Statistical Assistance for Programme Selection – For a Better Targeting of Active Labour Market Policies in Switzerland. CESifo DICE Report 2/2006.

Bimrose, J., S.A. Barnes, A. Brown, C. Hasluck & H. Behle. (2007). *Skills Diagnostics and Screening Tools: A literature Review*. Department for Work and Pensions, Research Report No. 459.

Black, D.A., M.C. Berger & J. Smith. (2001). Evaluating Profiling as a Means of Allocating Government Services. In Lechner, M. & P. Friedhelm (eds.), *Econometric Evaluation of Active Labour Market Policies*, Heidelberg: Physica.

Black, D.A., J.A. Smith, M. Plesca & S. Shannon. (2003). *Profiling UI Claimants to Allocate Remployment Serivces: Evidence and Recommendations for States*, US Department of Labour Employment and Training Administration (*wdr.doleta.gov/opr/fulltext/*).

Bryson, A., & D. Kasparova (2003). Profiling Benefit Claimants in Britain: A Feasibility Study. Department for Work and Pensions, Research Report No 196 (http://www.dwp.gov.uk/asd/asd5/rports2003-2004/rport196/Main.pdf).

De Koning, J. & B. Van Dijk. (2004). *A Profiling System for the Unemployed in Slovakia*. Paper for the TLM Meeting on Active Labour Market Policies, April 26 and 27, Rotterdam.

Denny, K., Harmon, C. & O’Connell, P. (2000). Investing in People: The Labour Market Impact of Human Resource Interventions Funded by the Structural Funds. Dublin: ESRI Policy Research Series.

Fahr, R. & U. Sunde. (2006). Did the Hartz Reforms Speed-Up Job Creation? A Macro-Evaluation Using Empirical Matching Functions. IZA Discussion Paper 2470.

Frölich, M., M. Lechner & H. Steiger. (2003). Statistically Assisted Programme Selection – International Experiences and Potential Benefits for Switzerland. *Swiss Journal of Economics and Statistics*, *139* (3), 311-331.

Gibbins, C. (1997). *Early Identification Pilots: Results at 12 Months*. Employment Service, REB113.

Hasluck, C. (2008). The Use of Statistical Profiling for Targeting Employment Services: The International Experience. In Di Domenico, G. & S. Spattini (eds.), *New European Approaches to Long-Term Unemployment: What Role for Public Employment Services and What Market for Private Stakeholders?*, The Netherlands: Kluwer Law International.

Lechner, M. & J. Smith. (2007). *What* is the Value Added by Case Workers?. *Labour Economics*, 14 (2), 135-151.

Lipp, R. (2005). Job Seeker Profiling: The Australian Experience. *Paper Presented at EU-Profiling Seminar*, Nuremburg, January 2005.

O'Connell**,** P. (2002) "Are they Working? Market Orientation and the Effectiveness of Active Labour Market Programmes in Ireland", *European Sociological Review*, Vol. 18.

OECD (1999). *The Public Employment Service in the United States*. Paris: Organisation for Economic Cooperation and Development.

Rosholm, M., J. Staghøj, M. Svarer & B. Hammer. (2006). A Danish Profiling System, *Danish Economic Journal* (*Nationaløkonomisk Tidsskrift*), 144 (2), 209-229.

Wandner, S. (1998). Worker Profiling and Re-employment Services in the United States, in *Early Identification of Jobseekers at Risk of Long-term Unemployment: The Role of Profiling*. Paris: Organisation for Economic Cooperation and Development.

Wells, B. (1998). Early Identification/Profiling in the United Kingdom, in *Early Identification of Jobseekers at Risk of Long-term Unemployment: the Role of Profiling*. Paris: Organisation for Economic Cooperation and Development

Appendix

Table A1: Marginal Effects for Binary Probit Models of Male Claimants Leaving the Live Register to Employment

Variables	Six-Month	Twelve-Month	Fifteen-Month
Age Reference Category: Aged 18-24			
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)
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)
Education Reference Category: Primary or Less			
Junior Cert	0.022	0.002	0.002
	(0.015)	(0.012)	(0.012)
Leaving Cert	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)

Table A1 continued:

Variables	Six-Month	Twelve-Month	Fifteen-Month
Literacy/Numeric 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 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)
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 5yrs	0.057***	0.044***	0.045***
	(0.010)	(0.009)	(0.009)
Signing for 12mths+	-0.179***	-0.166***	-0.159***
	(0.012)	(0.012)	(0.012)
CES Previous 5yrs	-0.070**	-0.070***	-0.090***
	(0.031)	(0.027)	(0.027)
On CES for 12mths+	-0.108***	-0.071**	-0.053**
	(0.038)	(0.035)	(0.035)
Social Welfare Payment Type Reference Category: Unemployment Credits			
Jobseekers Allowance	-0.048	0.014	0.022
	(0.031)	(0.028)	(0.027)
Jobseekers Benefit	0.142***	0.194***	0.200***
	(0.030)	(0.027)	(0.027)

Table A1 continued:

Variables	**Six-Month**	**Twelve-Month**	**Fifteen-Month**
Number of Claims	-0.271***	-0.085	-0.092*
	(0.090)	(0.053)	(0.051)
Location Reference Category:			
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)
Near Public Transport	0.018	0.019*	0.022**
	(0.013)	(0.011)	(0.011)
Observations	14,737	17,738	17,552
Pseudo R^2	0.1274	0.1150	0.1209

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

Year	Number	Title/Author(s) ESRI Authors/Co-authors Italicised
2010		
	344	The Economic Crisis, Public Sector Pay, and the Income Distribution *Tim Callan,* Brian Nolan (UCD) and *John Walsh*
	343	Estimating the Impact of Access Conditions on Service Quality in Post *Gregory Swinand, Conor O'Toole* and *Seán Lyons*
	342	The Impact of Climate Policy on Private Car Ownership in Ireland *Hugh Hennessy* and *Richard S.J. Tol*
	341	National Determinants of Vegetarianism *Eimear Leahy, Seán Lyons* and *Richard S.J. Tol*
	340	An Estimate of the Number of Vegetarians in the World *Eimear Leahy, Seán Lyons* and *Richard S.J. Tol*
	339	International Migration in Ireland, 2009 *Philip J O'Connell* and *Corona Joyce*
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