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POLICY PAPER

The Impact of Training Programme Type and Duration on the Employment Chances of the Unemployed in Ireland

SEAMUS McGUINNESS
The Economic and Social Research Institute, Dublin
Trinity College Dublin
National Institute of Labour Studies, Flinders University, Australia
IZA – Institute for the Study of Labor, Bonn, Germany

PHILIP J. O'CONNELL
University College Dublin

ELISH KELLY
The Economic and Social Research Institute, Dublin
Trinity College Dublin

Abstract: In the extensive literature on the employment impact of public sponsored training programmes for the unemployed, insufficient attention has been paid to the differential impact of different types of training programmes and of their varying duration. This paper uses a unique dataset, which tracks the labour market position of a cohort of unemployment benefit claimants for almost two years, to evaluate the impact of a range of government sponsored training courses in Ireland. Overall, we found that those who participated in training were less likely to be unemployed at the end of the two year study period. However, the average effect of training varied by the type and duration of training received. We found strong positive effects for job search skills training and medium to high level skills courses, a more modest positive effect for general vocational skills programmes (which are not strongly linked to demand in the labour market) and less consistent effects with respect to low level skills training. We also found that training episodes with lower duration had a more positive impact, with the exception of high level skills training programmes where longer training durations appear more effective. We ensure the robustness of our results by employing propensity score matching to reduce the impact of non-random assignment of programme participants, and estimate generalised propensity scores to estimate dose response functions.

I INTRODUCTION

The evolution of the Irish recession that began in 2008 has been well documented, with much commentary focused upon the collapse of the banking system, the bursting of the property bubble and the escalating public sector deficit. As a consequence of these various factors, the unemployment rate in Ireland increased dramatically from less than 5 per cent in 2007 to 15 per cent in 2012. Irish policymakers are now faced with a Herculean task to reduce the level of unemployment. This task is particularly challenging given the growth in both the numbers of structurally unemployed construction sector workers and those that are long-term unemployed,[1] not to mention severe shortages of resources to tackle unemployment because of the fiscal crisis of the state and sluggish economic growth prospects in the medium term. Given this context, it is crucial that the limited public funds available in Ireland for labour market activation are used effectively. In relation to this matter, it would appear that much needs to be done in light of an evaluation of the country's activation programme, the National Employment Action Plan (NEAP), which concluded that the job search assistance (JSA) process implemented under the NEAP was wholly ineffective and, if anything, tended to impede an effective return to employment (McGuinness, O'Connell, Kelly and Walsh, 2011). That evaluation also concluded, however, that those who participated in training under the NEAP were less likely to be unemployed over a 21 month time horizon. Since then a number of policy changes have been introduced to bring Ireland's activation strategies closer into line with international best practices. However, it must be stated that the pace of change has been particularly slow given the alarming rise in the numbers of long-term unemployed.

The literature examining the impact of training programmes for the unemployed tends to pay insufficient attention to differences in the nature and duration of programmes. This paper seeks to inform policy and to fill that gap by examining the impact of different types and durations of training programmes on participants' subsequent employment performance, as measured by presence on or absence from the Live Register.[2] The study is based on a high quality dataset, consisting of an amalgamation of data from administrative

[1] Long-term unemployment, referring to those continuously unemployed for 1 year or more, accounted for 60 per cent of total unemployment in the final quarter of 2012 compared with 24 per cent in the final quarter of 2008 (Central Statistics Office (CSO), 2009 and 2013).

[2] The Live Register provides a monthly series of the numbers of people (with some exceptions) registering for unemployment-related social welfare payments or for other statutory entitlements at local offices of the Department of Social Protection. The Live Register is an administrative count and is not designed as a measure of unemployment.

sources and a comprehensive survey that followed welfare recipients from September 2006 until June 2008. The high quality of our data limits the influence of sample selection biases. From a policy perspective, the work presents a reliable and timely picture of the short-term pay-offs to various combinations of labour market training that will be informative, both from an Irish and international perspective, as governments throughout the developed world attempt to tackle the high unemployment problem that emerged after the Great Recession.

II LABOUR MARKET ACTIVATION IN IRELAND

A limited activation programme targeting youth unemployment was introduced in Ireland in 1996. However, the use of activation measures began in earnest in September 1998 when the 'Preventative Strategy' was introduced under the National Employment Action Plan (NEAP).[3] Under the NEAP process, targeted groups of unemployment-related social welfare payments – those on either Jobseeker's Allowance (JA) or Jobseeker's Benefit (JB)[4] – were to be interviewed after a period of 13 weeks on the Live Register. After this point, jobseekers were referred by the benefit agency, the Department for Social Protection (DSP), to the national training and employment authority, FÁS,[5] for an activation interview. Until a series of reforms introduced since 2010, Ireland was one of a small number of OECD countries where the placement function of the Public Employment Service (PES) was separate from the benefit function (Grubb, Singh and Tergeist, 2009). The NEAP activation interview was designed to initiate a process whereby FÁS assisted the unemployed individuals to achieve employment via additional services, including guidance and counselling, establishment of action plans, and provision of employment and/or training programmes, work placement and/or job offers. Referral to training was one outcome of the NEAP activation process when the data for this paper were collected in the years 2006-2008.

[3] The NEAP was developed by the Irish government in response to the European Employment Strategy (EES). This strategy required each member state to develop a National Action Plan (NAP) setting out the actions that the country would undertake to implement the guidelines contained in the EES (Grubb, Singh and Tergeist, 2009). The Irish government developed its 'Preventative Strategy' (i.e., activation strategy) to meet the specific EES guideline of improving employability via a more systematic engagement of the employment services with the unemployed.

[4] JA and JB are Ireland's two unemployment benefits. JA is a means-tested payment and JB is based on social insurance contributions.

[5] FÁS has been disbanded. In January 2012, the organisation's employment services and employment programmes were transferred to the Department of Social Protection, and its training function was taken over by the Department of Education and Skills in 2014.

III RESEARCH EVIDENCE ON THE IMPACT OF TRAINING PROGRAMMES

The objective of training programmes offered to jobseekers is to enhance their human capital, and, therefore, employment prospects. Programmes vary according to jobseeker type. For example, some individuals require basic job search training and/or other general skills, while others undertake more intensive and specific training to enhance their employability or to secure better quality jobs. Training tends to account for the largest share of spending on active labour market policy measures (Martin, 2000). However, the findings from the empirical literature on the effectiveness of training programmes are mixed, even when long-run effects are considered. Given that the focus of this study relates to the inter-relationship between training duration and training type, we will briefly review the literature in these areas.

The evidence is mixed regarding the impact of training programmes targeting the unemployed. Many studies have found positive average treatment effects of participation in training programmes on employment/unemployment, such as Cockx (2003), Richardson and van den Berg (2006), Fitzenberger, Osikominu and Völter (2006), Lechner, Miquel and Wunsch (2007), Lechner and Wunsch (2009), Fitzenberger, Osikominu and Paul (2010), and Lechner, Miquel and Wunsch (2011). However, many other studies have reported negative or insignificant impacts e.g. Rosholm and Skipper (2009), Crépon, Ferracci and Fougère (2011), Lechner (2000) and Hujer and Wellner (2000). Calmfors, Forslund and Hemstrom (2006) in their review of ALMPs in Sweden argue that evaluations of training acquired in the 1980s suggested positive results, but training in the 1990s usually found insignificant or negative results, particularly when account was taken of selection effects.

Results from evaluations focusing on the impact of the duration of training on labour market outcomes have also been inconclusive. In France, Crépon *et al.* (2011) found that longer training spells led to longer unemployment spells but also to longer employment spells. Fitzenberger *et al.* (2010) found a similar result for Germany, in that longer duration public-sponsored training programmes had higher long-run employment gains. Kluve, Schneider, Uhlendorff and Zhao (2007), again for Germany, found positive employment effects for training programmes with durations of up to three months, but programmes longer than this did not add any additional benefits (see also Biewen, Fitzenberger, Osikominu and Waller, 2007). Hujer, Thomsen and Zeiss (2006), on the other hand, found no impact for short-term vocational training programmes, while medium (six month) and long length (twelve month) programmes had negative employment effects.

A series of papers on Germany's experience with training provide useful evidence regarding the differential impact of different types of training programmes. Biewen *et al.* (2007) in their analysis of the impact of short-term training programmes, found that 'practical' orientated courses performed better than 'classroom' training. Lechner *et al.* (2010) found that 'retraining', for up to two years for a different professional qualification, had the biggest employment impact seven years after programme start, followed by short-duration (about five months) and long-duration (9 to 12 months) training to provide additional qualifications in a current profession. For East Germany, Fitzenberger and Völter (2007) found that training in specific professional skills and techniques to enhance qualifications in a current occupation produced positive medium (1-3 years) and long-run (4-6 years) employment effects. However, neither practice firms nor retraining for a different occupation showed consistent positive employment effects.

Sianesi (2008) found that unemployed individuals in Sweden that participated in a training programme subsequently displayed lower employment rates, along with higher benefit dependency. Wage subsidies, on the other hand, increased employment prospects in the long-term. Overall, Sianesi (2008) concluded that ALMPs that resemble regular employment perform better. An earlier study of Swedish ALMPs by Carling and Richardson (2004) found that subsidised work experience and training provided by firms had better outcomes than classroom vocational training. Arellano (2010) examined a variety of training courses in Spain and found that 'medium-level' programmes, including occupational training for unskilled workers, and specialist training for skilled workers, reduced the length of unemployment spells, with stronger effects for females.

Compared to many other OECD countries, there is a shortage of rigorous evidence on the impact of training in Ireland. O'Connell (2002) and O'Connell and McGinnity (1997) found that programmes with strong linkages to the labour market, including both training and employment-subsidy schemes, were more likely to enhance the employment prospects of their participants. In relation to training programmes delivered during the 1990s, they found that training in specific skills was more likely to increase participants' subsequent probability of employment. This is consistent with the Swedish findings by Sianesi (2008) and Carling and Richardson (2004).

From the broader international perspective, the results of recent meta-studies by Kluve (2006) and Card, Kluve and Weber (2010) are also informative. The main policy implication from both Kluve (2006) and Card *et al.* (2010) is that 'programme type' is an important influence of programme effectiveness. In this regard, it would appear that training programmes that are targeted to specific groups, and which involve some type of on-the-job component, and, as such, are closely related to the labour market, tend to show positive employment effects, while unfocused large-scale training programmes are less successful in improving the employment prospects of their participants.

IV DATA AND METHODS

The dataset used in this study is quite exceptional in both construction and content, and comes from three key administrative sources and a specially designed survey:

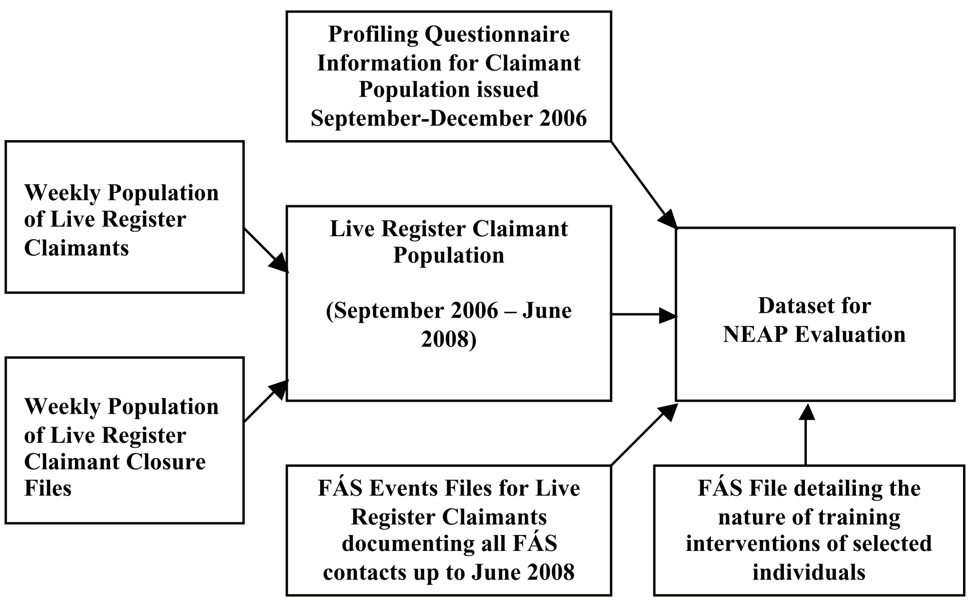
(i) The Live Register database, which contains information on all unemployment-related social welfare recipients in Ireland, consists of weekly files detailing (a) the claimant population and (b) claimants leaving the Live Register each week;[6]
(ii) The FÁS Events and Customer files, which chronicle each jobseeker's contact with the employment and training agency;
(iii) An administrative datafile, specifically compiled by the DSP, detailing the specific training programmes undertaken by activated individuals within our sample who entered FÁS training programmes prior to week 35 on the Live Register;
(iv) The DSP's profiling datafile, which contains employment, unemployment and benefit history information, along with comprehensive socio-economic details, collected in a specially designed questionnaire administered to all individuals that registered a new claim for an unemployment-related social welfare benefit during a 13 week period between September and December 2006. The administration of this survey was a once-off event designed to facilitate the development of an unemployment profiling model for Ireland.[7]

The general approach to the construction of the sample used in the analysis is outlined in Figure 1. The Live Register information was constructed using weekly files provided to us by the DSP for the period September 2006 to June 2008 for a population of individuals who made claims for unemployment-related social welfare payments in the designated 13 week period between September and December 2006 during which the profiling

[6] The Live Register database contains detailed information on benefit recipients marital status, geographic location (i.e., social welfare office where the claimant signs on the Live Register) and spousal earnings.
[7] For more information, see O'Connell, McGuinness, Kelly and Walsh (2009).

questionnaire was administered. The Live Register database was then merged with the DSP's profiling datafile and the FÁS customer events file to generate the final database on which the evaluation was based. From the evaluation database, we drew a treatment population of individuals not previously intervened with under the NEAP that were referred to FÁS and who subsequently undertook training. The outcomes in respect of this population were compared with those for a control group that consisted of individuals who had been referred to FÁS but had received Job Search Assistance (JSA) only. The use of such a control group enables us to effectively isolate the impact of training on employment prospects, given that training participation represents the only observed distinguishing factor between the treatment group, which received a NEAP activation interview followed by training, and a control group that received a NEAP activation interview only. Furthermore, in order to account for the impacts of dynamic bias, we follow Sianesi (2004) by defining the control group as all individuals who did not participate in treatment up to a certain time point. The cut-off point for inclusion within the control grouping was week 35 on the Live Register. In order to evaluate the impact of training, we utilise data spanning the entire period over which the profiling database individuals were tracked, which was September 2006 up to June 2008.

Figure 1: *Construction of NEAP Evaluation Dataset*



The total number of unemployment payment claimants that joined the initial Live Register database over the 13 week period between September and December 2006 was 60,189. However, over 15,000 individuals failed to complete the DSP's profiling questionnaire. When account was taken of this, and duplicates and claim types ineligible for NEAP assistance were eliminated as well, our NEAP evaluation sample fell to 27,328. Of our 27,328 NEAP sample, 9,817 received NEAP activation interviews during the study period, which comprise the central population used in this study. A total of 1,505 of those interviewed were 'closed' from the Live Register to participate in FÁS training programmes. There were significant numbers of unemployed people participating in various education programmes at this time, mainly under the Back to Education Allowance scheme and the Vocational Training Opportunities Scheme implemented by the Department of Education and skills. Most of these schemes entailed return to long-term full-time education, so insufficient time would have elapsed post-programme for us to evaluate their impact in this analysis. Accordingly, such back-to-education participants are absent from both the treatment and the control groups and the evaluation focuses exclusively on FÁS training.

FÁS training courses typically last less than six months; thus, we restrict our treatment group to individuals who exited the Live Register for such a programme prior to week 35 to allow adequate time to elapse for individuals that participated in training to have either entered employment or, having failed to do so, to have re-entered the Live Register. Given our data restrictions, we are unable to assess the medium or long-term effects of training. However, from a public policy perspective, whereby the objective of the training intervention is to achieve an improvement in employment chances, the short-run effects are clearly important. We restrict our control group to individuals with minimum unemployment durations of 20 weeks who were interviewed but not trained, on the grounds that the treatment group would generally have been on the Live Register for at least this period before exiting to training. When we apply the restriction that the training intervention had to occur at or before week 35 of the study, our treatment group is reduced from 1,505 to 764 individuals, and the remaining 741 individuals that received training after week 35 are added to the control group. Therefore, individuals in the control group may have enrolled in training at some later point in their unemployment spell. This dynamic framework reflects the decision process facing claimants i.e., whether to participate in training now or postpone it to a later point in the event that their attempts to find employment are unsuccessful. When we link the data with the detailed training information provided to us by FÁS, the number of valid matches falls to 636[8] individuals, which represents our key treatment sample.

As stated, our control group consists of individuals who received an activation interview with FÁS but no training. We apply some further restrictions to the data, such as removing individuals still in employment at the time of their claim,[9] after which the "interviewed only" control group consists of 8,088 individuals, just under 70 per cent of whom became NEAP clients for the first time during the course of the current study. We also exclude from the control group individuals who exited to employment and then subsequently re-entered the Live Register. However, when we relax this assumption our results remain largely unchanged.[10]

We evaluate the impact of training in terms of an absence from the Live Register at one point in time, specifically 21 months (91 weeks from the beginning of the Profiling data capture): 21 months is the latest available data point, and we used the last observation in order to reduce the impact of lock-in effects. Van Ours (2001) points out that the observed impact of an ALMP will be the net of two countervailing effects. The first relates to the participant's increased employability through, in this case, additional training, while the second relates to a reduced employment probability as a consequence of reduced job search while undertaking the training programme. By observing an individual's status at week 91, we allow for a sufficient period of time to elapse after programme participants had completed their training. Over 90 per cent of the treatment group had completed their training programmes by December 2007, implying that the vast bulk of the treatment group had a minimum of 6 months to look for a job after completing their training, thus ensuring that lock-in effects are minimal.

Based on the course descriptions provided to us by the DSP, we categorised training episodes into the following five groups: (i) Job Search Training, (ii) General Training, (iii) Low-level Specific Skills Training, (iv) Medium-level Specific Skills Training and (v) High-level Specific Skills Training (Table 1).

JobSearch Training refers to short training programmes in job seeking, application and interview techniques. General Training captures vocational skills training that lacks a strong linkage to the labour market or to a particular occupation; for example, training for the European Computer

[8] We were forced to make further exclusions as some individuals received more than one period of training; thus, we concentrated on the final training episode and excluded individuals who's final training episode ended close to June 2008.

[9] Under Ireland's social welfare system, individuals are entitled to work a limited number of hours per week without losing their entitlement to benefits.

[10] Results available from the authors.

Table 1: *FÁS Training Programmes*

	Type of Training	*Description*	*Example*
1	Job Search Training	Training in job search techniques	*Preparing for Work*
2	General Training	General purpose training without specific link to labour market	*European Computer*
3	Specific Skills Training	Training for specific occupational position	
4	– Low-Level		*Introduction to Warehousing and Distribution*
5	– Medium-Level		*Computerised Accounts and Payroll*
6	– High-Level		*Computer Aided Draughting and Design*

Driving Licence (ECDL). Specific Skills Training has a stronger linkage to the labour market and previous research (Sianesi, 2008; Carling and Richardson, 2004; O'Connell, 2002; and O'Connell and McGinnity, 1997) suggests that this type of training should have a stronger impact on participants' employment prospects. We distinguished between three levels of Specific Skills Training from Low-level (e.g., *Introduction to Warehousing and Distribution*) to High-level (e.g., *Computer Aided Draughting and Design*).

The range of potential methodological approaches to the evaluation of ALMPs includes matching estimates, duration models and difference-in-difference estimates. We opt for a standard probit analysis augmented by a matching based approach as it has several advantages over duration models. Specifically, it (i) facilitates a more straightforward mechanism to account for sample selection bias; (ii) seems more sensible given that the nature of the study restricts us to examining outcomes at a single point in time; and (iii) allows for the straightforward calculation of relevant marginal effects. The difference-in-difference approach relies on a dataset in which we observe both a treatment and control group in two periods. In the present study the difference-in-difference approach is inappropriate on the grounds that eligibility for training assistance would be inextricably linked to an unbroken period of unemployment prior to the claimant receiving support; thus there will, by definition, be no variation in the outcomes of the treatment group in the early period of the data.

V RESULTS

Table 2 reports the duration of programmes by programme type. It should be noted that the data relates to observed as opposed to planned durations; therefore, it is unclear if the job-seeker left the programme prior to completion in order to take up employment. There is some variation in the average duration of training programmes. Perhaps not surprisingly, job search training courses have the shortest duration and high-level specific skills training the longest. Taking average duration of training (measured in terms of weeks) into account, just over 40 per cent of training effort is in general training, with weak links to the labour market, and almost 30 per cent is in low-level specific skills, 20 per cent is in medium- or high-level specific skills, and 8 per cent takes the form of job search training. No information on training costs is available. However, on the basis that training costs may tend to rise with skill intensity, the share of spending on high- and medium-skill training is likely to exceed the share measured in terms of training weeks (Table 3).

Table 2: *Distribution of FÁS Training Programmes by Duration in Weeks and Skill Level*

	Average Duration	*Number*	*Per Cent*
Programme Type:			
Job Search Training	8	63	8
General Training	17	256	41
Specific Skills – Low	18	179	29
Specific Skills – Medium	19	98	16
Specific Skills – High	40	25	4
Total		621	100

Table 3: *Distribution of FÁS Training Programmes by Training Weeks*

	Training Weeks Numbers	*Per Cent*
Programme Type:		
Job Search Training	522	5
General Training	4,342	38
Specific Skills – Low	3,426	31
Specific Skills – Medium	1,893	17
Specific Skills – High	1,018	9
Total	11,201	100

With respect to our econometric analysis, we evaluate the effectiveness of public-sponsored training in a number of ways. We begin with an analysis of training participation per se and then proceed to examine the role of programme type and duration in more detail. All results are checked in terms of their robustness to the influences of both sample selection and unobserved heterogeneity. It should be noted that if an individual receives FÁS training as part of the NEAP, we would observe an interview referral from the DSP prior to the claim being closed for training purposes. However, individuals can also voluntarily enter a FÁS office on becoming unemployed and request training assistance. It is likely that such individuals, which we will hereafter refer to as "walk-ins", possess certain unobserved attributes, such as motivation and commitment to job search, which would upwardly bias the estimated treatment effect of training. Within our treatment group of trainees, we do not observe a DSP referral interview referrals for 185 individuals (29 per cent). Thus, we test the sensitivity of our results with such "walk-ins" removed. This second specification arguably provides a more robust estimate of the effects of training on exits from unemployment.

The initial results from our multivariate analysis are presented in Table 4. The first model evaluates the average impact of public-sponsored training on a participant's likelihood of exiting unemployment using a single dummy variable to represent participation in any training programme. The second specification measures the effect of the duration of training in weeks. These specifications are estimated for the entire sample and for the sub-sample excluding "walk-ins".[11] Generally, the models are well specified, with the large range of additional controls that are included in the specifications conforming to expectations. For example, the probability of an exit from unemployment by 21 months is positively related to possessing a third-level qualification, having one's own transport, a willingness to move for a job and having a high earning spouse. On the other hand, the likelihood of a successful exit is lowered by the presence of dependent children, a history of long-term unemployment, having literacy/numeracy problems and claiming Jobseeker's Allowance (JA).[12] In terms of our variables of interest, the results indicate that, relative to the control group, FÁS training increased a participant's likelihood of no longer being unemployed in June 2008 by 10 per cent on average, or by 3 per cent for every ten weeks training undertaken. The

[11] The treatment group size is now 640 as opposed to 764.

[12] Claimants will receive JA on the basis of a means test. However, provided that claimants have made sufficient PRSI contributions they may qualify for Jobseeker's Benefit (JB), which is a social insurance-based, non means-tested social welfare payment. JB represents the base case in the models, suggesting that claimants with a recent history of labour market attachment have a higher likelihood of exiting to employment.

estimate relating to the binary measure falls slightly when the models are re-estimated on the sample excluding "walk-ins", although, the differences are marginal. The training duration variable is no longer significant within the model that excludes potential walk-ins. However, the estimate is somewhat crude as it does not allow for a non-linear relationship between duration and exit rates, a matter we will return to later in the paper.

Table 4: *Overall Estimated Impact of FÁS Training on Exits from the Live Register at 21 Months*

	Total Sample		*Walk-ins Excluded*	
Training Type:				
FÁS Training	0.100***		0.079***	
	(0.021)		(0.024)	
Training Duration		0.003***		0.001
		(0.001)		(0.001)
Personal Information:				
Male	–0.010	–0.012	–0.011	–0.012
	(0.012)	(0.012)	(0.012)	(0.012)
Aged 25-34	0.001	–0.000	0.003	0.002
	(0.016)	(0.016)	(0.016)	(0.016)
Aged 35-44	–0.032*	–0.034*	–0.032*	–0.033*
	(0.019)	(0.019)	(0.019)	(0.019)
Aged 45-54	–0.060***	–0.060***	–0.060***	–0.060***
	(0.022)	(0.022)	(0.022)	(0.022)
Aged 55 plus	–0.089***	–0.088***	–0.088***	–0.088***
	(0.026)	(0.026)	(0.026)	(0.026)
Married	0.039**	0.039**	0.039**	0.039**
	(0.019)	(0.019)	(0.020)	(0.020)
Cohabits	–0.017	–0.018	–0.017	–0.018
	(0.027)	(0.027)	(0.027)	(0.027)
Separated/Divorced	0.030	0.031	0.033	0.033
	(0.029)	(0.029)	(0.029)	(0.029)
Widowed	0.177***	0.177***	0.196***	0.197***
	(0.065)	(0.065)	(0.065)	(0.065)
Children	–0.036***	–0.036***	–0.036***	–0.036***
	(0.009)	(0.009)	(0.009)	(0.009)
Human Capital:				
Junior Certificate	–0.020	–0.019	–0.020	–0.019
	(0.018)	(0.018)	(0.018)	(0.018)
Leaving Certificate	0.030*	0.032*	0.030	0.032*
	(0.018)	(0.018)	(0.018)	(0.018)
Third-level	0.114***	0.115***	0.115***	0.116***
	(0.020)	(0.020)	(0.020)	(0.020)

Table 4: *Overall Estimated Impact of FÁS Training on Exits from the Live Register at 21 Months (Contd.)*

	Total Sample		*Walk-ins Excluded*	
Apprenticeship	–0.005	–0.006	–0.005	–0.006
	(0.016)	(0.016)	(0.016)	(0.016)
Literacy/Numeracy Problems	–0.047**	–0.047**	–0.051**	–0.051**
	(0.021)	(0.021)	(0.021)	(0.021)
English Proficiency	–0.002	–0.001	–0.001	–0.001
	(0.030)	(0.030)	(0.030)	(0.030)
Location:				
Village	0.009	0.008	0.010	0.010
	(0.020)	(0.020)	(0.020)	(0.020)
Town	0.003	0.004	0.003	0.004
	(0.018)	(0.018)	(0.019)	(0.019)
City	–0.006	–0.005	–0.005	–0.004
	(0.019)	(0.019)	(0.019)	(0.019)
Transportation:				
Own Transport	0.028**	0.028**	0.027**	0.027**
	(0.013)	(0.013)	(0.013)	(0.013)
Public Transport	–0.007	–0.007	–0.008	–0.008
	(0.016)	(0.016)	(0.016)	(0.016)
Employment History:				
Employed in Last Month	0.039	0.035	0.045	0.042
	(0.031)	(0.031)	(0.032)	(0.032)
Employed in Last Year	0.036	0.033	0.041	0.038
	(0.031)	(0.031)	(0.032)	(0.032)
Employed in Last 5 Years	0.011	0.009	0.019	0.018
	(0.033)	(0.033)	(0.033)	(0.033)
Employed Over 6 Years	–0.024	–0.026	–0.021	–0.023
	(0.040)	(0.040)	(0.041)	(0.041)
Job Duration:				
Job Duration Less 1 Month	–0.010	–0.007	–0.014	–0.011
	(0.036)	(0.035)	(0.036)	(0.036)
Job Duration 1-6 Months	0.039	0.041	0.033	0.035
	(0.029)	(0.029)	(0.030)	(0.030)
Job Duration 6-12 Months	0.031	0.033	0.028	0.029
	(0.031)	(0.031)	(0.032)	(0.032)
Job Duration 1-2 Years	0.044	0.046	0.041	0.043
	(0.032)	(0.032)	(0.032)	(0.032)
Job Duration 2+ Years	0.044	0.047	0.044	0.045
	(0.030)	(0.030)	(0.030)	(0.030)
Would Move for a Job	0.033***	0.033***	0.034***	0.034***
	(0.012)	(0.012)	(0.012)	(0.012)
UE Benefit Type:				
Job Seeker's Assistance	–0.170***	–0.171***	–0.170***	–0.170***
	(0.014)	(0.014)	(0.014)	(0.014)

Table 4: *Overall Estimated Impact of FÁS Training on Exits from the Live Register at 21 Months (Contd.)*

	Total Sample		*Walk-ins Excluded*	
Signing on for 12 Months+	–0.071***	–0.070***	–0.072***	–0.071***
	(0.018)	(0.018)	(0.018)	(0.018)
Weekly Spousal Earnings:				
Spousal Earnings €250	0.130***	0.129***	0.138***	0.137***
	(0.029)	(0.029)	(0.030)	(0.030)
Spousal Earnings €251-350	0.076	0.073	0.078	0.076
	(0.080)	(0.080)	(0.080)	(0.080)
Spousal Earnings €351+	0.083***	0.081***	0.087***	0.086***
	(0.022)	(0.022)	(0.022)	(0.022)
Historic FÁS Client	–0.055***	–0.054***	–0.051***	–0.050***
	(0.014)	(0.014)	(0.014)	(0.014)
Observations	9,417	9,417	9,248	9,248
Pseudo R^2	0.081	0.080	0.081	0.080

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.

In Table 5, the single dummy variable representing participation in training is replaced with five dummy variables distinguishing the type of training received. We find positive effects in respect of each of the training programmes when the model is estimated on the entire sample. The largest effects relate to high-level specific skills training, which, relative to the control group, increased the probability of an exit from the Live Register by 21 per cent, while medium-level specific skills training and job search training each increased the probability of exiting unemployment by between 15 and 16 per cent. The smallest effects relate to general training and low-level specific skills training, which increased the probability of exiting from unemployment by 6 and 7 per cent respectively. Within the more robust restricted sample that excludes “walk-ins”, significant impacts were derived for all courses apart from low-level specific skills training. The positive effect for medium-level skills training was weaker in this specification while the estimates for high-skill, general and job-search training increased slightly.

To ensure the robustness and reliability of our results, we undertake a number of sensitivity checks. First, we guard against the possibility of non-random assignment to the treatment group. If assignment to training was in some way systematic, for example, if individuals with superior (inferior) human capital characteristics were more (less) likely to be assigned to the treatment by case workers, then failure to take account of such non-random assignment would upwardly (downwardly) bias the estimated impact of training. Evaluation studies of this kind typically deal with this issue by

Table 5: *Impacts of Training on Probability of Exiting the Live Register at 21 Months by Training Type*

	Total Sample		*Walk-ins Excluded*	
Training Type:				
All Training	0.100***		0.079***	
	(0.021)		(0.024)	
JS Training		0.152**		0.179***
		(0.059)		(0.063)
General		0.065**		0.090**
		(0.032)		(0.038)
Specific Skills – Low		0.075**		0.020
		(0.038)		(0.046)
Specific Skills – Medium		0.159***		0.102*
		(0.050)		(0.060)
Specific Skills – High		0.210***		0.224**
		(0.073)		(0.087)
Observations	9,417	9,417	9,248	9,248
Pseudo R^2	0.081	0.081	0.081	0.082

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

employing a Propensity Score Matching (PSM) estimation framework in order to ensure that treated individuals are compared with members of the control group who hold similar observable characteristics. PSM involves a two stage process. In the first stage, the principal characteristics that influence the probability of being in the treatment group are identified using a probit model, and individuals in both the treatment and control groups are then assigned a "propensity score" based on their estimated probability of receiving the treatment (i.e., FÁS training). In the second stage, individuals within the treatment group are "matched" with counterparts in the control group that have similar propensity scores and their actual outcomes (in this instance, actual exits from unemployment) are compared. It can be shown that matching individuals on the basis of propensity scores is equivalent to matching on actual characteristics (Rosenbaum and Ruben, 1983). There are a number of PSM algorithms that can be estimated and, while each has advantages and drawbacks, no single method is generally considered to be superior. In this instance, we employ a Kernel estimator.

The propensity score is defined in a seminal work by Rosenbaum and Rubin (1983) as the conditional probability of receiving a treatment given certain determining characteristics:

$$p(X) = \Pr\{D = 1/X\} = \{E(D/X\} \tag{1}$$

where D is a binary term indicating exposure to the treatment (in this case FÁS training) and X is a vector of determining characteristics drawn from our profiling data. Given a population of units denoted by i, if the propensity score $p(X_i)$ is known, then the Average Effect of the Treatment on the Treated (ATT) can be estimated as follows:.

$$T = E\{Y1_i \quad Y0_i/D_i = 1\} \tag{2}$$

$$T = E\{E\{Y1_i \quad Y0_i/D_i = 1, p(X_i)\}\} \tag{3}$$

where the outer expectation is over the distribution of $(p(X_i) \mid D_i = 1)$ and $Y1_i$ and $Y0_i$ are the potential outcomes in the two counterfactual situations of the treatment and non-treatment respectively. Our models are estimated using the psmatch2 procedure in stata (Becker and Inchino, 2002).[13] The ATT is estimated across a region of common support.[14]

A principal problem with the application of PSM in this instance is the relatively small size of the treatment groups that are being matched against the control group and, more specifically, the low numbers undertaking job search training and medium-level and high-level specific skills training. To overcome this problem, we pool the medium-level and high-level specific skills training participants, which seems sensible given the broad similarity of the marginal effects of both types of training within the probit analysis. Given the small number of individuals that undertook job search training, it is not feasible to undertake PSM for such trainees. Furthermore, the more restricted size of the treatment sample excluding "walk-ins" means that the PSM analysis by training type is not feasible. However, a PSM model is estimated on the overall training effect to test for sample selection within this cohort. We ensure that the common support condition is fulfilled, thus ensuring that all possible combinations of characteristics that can be observed within the treatment group can also be observed within the control group (Bryson, Dorsett and Purdon, 2002). This condition is met by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls.

[13] The notation used replicates that of Becker and Inchino (2002).
[14] Treated units with a proposensity score higher than the largest score in the untreated pool are left unmatched.

As our estimated treatment effect is conditioned on the propensity score, we next check to ensure that the assumption that this is equivalent to conditioning on the individual covariates was met. In essence, this amounts to testing that all observable differences between the control and treatment groups have been eradicated post-matching, thus ensuring that any additional conditioning on observable characteristics will not provide any new information on the treatment decision. We undertake a number of post-estimation checks including ensuring that statistically significant differences within individual characteristics across the treated and untreated samples are eradicated post-matching. We also measure the extent to which the pseudo R^2 of the stage 1 probit falls towards zero when estimated within the matched sample. Our analysis confirms that our data are well-balanced[15] and, therefore, we are confident that like-for-like comparisons with regards to the observable characteristics in our data are achieved within the matching framework.

Table 6: *Probit and PSM Estimates of Training Effects*

	Total Sample	*Walk-ins Excluded*
Probit – All training	0.100 (0.021)***	0.079 (0.024)***
PSM (Kernel) – All training	0.091 (0.020)***	0.062 (0.034)***
Probit – General training	0.065 (0.032)**	
PSM (Kernel) – General training	0.055 (0.031)*	
Probit – Low-level skills training	0.075 (0.038)**	
PSM (Kernel) – Low-level skills training	0.059 (0.036)*	
Probit – Medium/high-level skills training	0.180 (–)***	
PSM (Kernel) – Medium/high-level skills training	0.187 (0.039)***	

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

The reliability of any propensity score matching estimate is dependent upon the Conditional Independence Assumption (CIA) being met i.e., that selection to the treatment is based solely on observables within the dataset and that all variables that simultaneously impact both the treatment and outcome variable are also observed. As the process of assignment to the treatment will effectively be based around a combination of each individual's education, labour market experience, age, unemployment history, family

[15] Results available from the authors.

situation, location, etc., all of which are observed within our data, we are confident that the variables at hand sufficiently incorporate all key aspects of the allocation to treatment process. Nevertheless, despite the richness of our data, it is not possible to completely rule out the possibility that our estimates are unaffected by one or more unobserved effects that simultaneously influence both the treatment and outcome variables. While we cannot explicitly eliminate such influences, as we might do for instance by estimating a fixed effects model within a panel environment, we can test the sensitivity of our estimated treatment effects to the presence of such hidden bias. We check our broad training PSM estimates (10.0 per cent for the entire sample and 7.9 per cent in the restricted sample) for robustness to unobservered heterogeneity bias using the "mhbounds" procedure in Stata (Table 7) and begin with the assumption of zero bias i.e., $\Gamma = 1$. The intuition here is that the results are robust to unobservables that positively impact both the likelihood of training and an exit from the Live Register and subsequently increase the odds ratio of treatment (termed positive selection bias) up to a factor of 1.10 ($\Gamma = 1.10$). The analysis reveals that, for the overall sample, our Kernel PSM estimate becomes statistically unreliable in the presence of an unobserved confounding factor that simultaneously increases the likelihood of receiving training and of exiting the Live Register by 30 per cent. This suggests that unobserved effects would need to be substantial for our estimate to become questionable. However, with respect to the restricted sample, the PSM estimate becomes insignificant in the presence of a confounding influence that simultaneously increases the probability of both events by 10 per cent. Thus, in conclusion, the results of our sensitivity checks confirm that while our estimates are generally robust to the presence of unobserved heterogeneity, some caution is still warranted. However, we believe the extensive range of variables already in our dataset reduces the likelihood of an unobserved confounding influence that would increase the odds ratio of receiving the treatment by more than 1:10.

The results from our previous models would seem to suggest that programmes of relatively short duration are most effective in terms of improving the employment outcomes of claimants. While there is a clear correlation between duration and training type, and bearing this caveat in mind, it is still of interest to examine the relationship between treatment duration and employment outcomes. To achieve a greater insight into the role of training duration, and to allow for non-linearity in its effect, we estimate a dose response function (DRF), which measures the impact of various doses of the treatment (i.e., training) on subsequent employment outcomes. It is again important to note that our durations relate to actual as opposed to potential training episodes. Thus, the analysis is prone to endogeneity bias whereby

Table 7: *Sensitivity of Overall PSM Estimates to Unobserved Heterogeneity*

	Total Sample		*Walk-ins Excluded*	
Gamma	*Q_mh+*	*p_mh+*	*Q_mh+*	*p_mh+*
1	3.983	0.000	1.994	0.023
1.05	3.399	0.000	1.488	0.068
1.1	2.844	0.002	1.005	0.157
1.15	2.314	0.010	0.545	0.293
1.2	1.808	0.035	0.105	0.458
1.25	1.323	0.093	0.221	0.412
1.3	0.858	0.195	0.627	0.265
1.35	0.410	0.341	1.018	0.154
1.4	–0.021	0.508	1.394	0.082
1.45	0.352	0.362	1.758	0.039
1.5	0.754	0.225	2.110	0.017
1.55	1.143	0.127	2.451	0.007
1.6	1.519	0.064	2.782	0.003
1.65	1.885	0.030	3.103	0.001
1.7	2.239	0.013	3.415	0.000
1.75	2.584	0.005	3.719	0.000
1.8	2.920	0.002	4.015	0.000
1.85	3.247	0.001	4.303	0.000
1.9	3.566	0.000	4.585	0.000
1.95	3.877	0.000	4.859	0.000
2	4.180	0.000	5.128	0.000

Note: Q_mh+ is the associate test statistic for each value of Γ and p_mh+ is the associated p value.

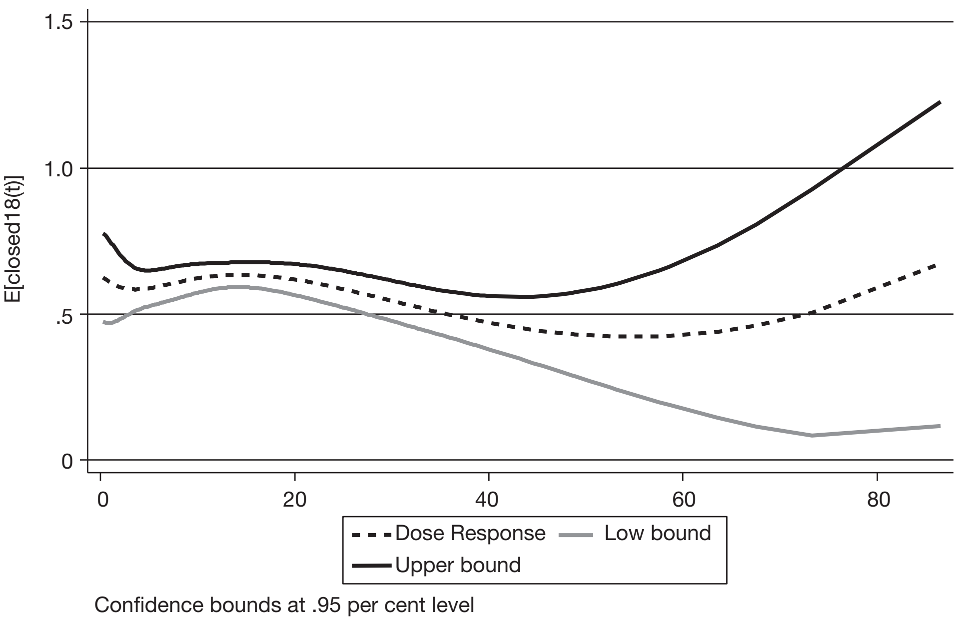
shorter durations may, themselves, be a product of a successful labour market outcome. Nevertheless, our previous results show that there is a clear and distinct relationship between training type and programme duration (Table 2), which suggests that the gap between potential and observed durations is likely to be small.[16] Furthermore, Kluve *et al.* (2007) using German data show little variation in the dose response functions estimated on potential and actual training durations. The dose response functions are estimated on the treated sample using the generalised propensity score (GPS). The technique was developed by Hirano and Inbems (2004) as an extension of the binary propensity score models estimated above. The GPS methodology separates treated individuals into segments related to their exposure to the treatment, in this instance days of training, and assumes that individuals within each strata of the GPS should have identical characteristics based on their

[16] Were this not the case then we would expect to see little or no variation in actual durations by course type.

propensity scores with respect to receiving treatment. Effectively, the approach ensures that assignment to training is random with respect to duration. The GPS methodology consists of three steps. In step one, the GPS for receiving treatment within each duration related interval is calculated and the data balanced both within and between intervals. In the second step, the relationship between the outcome variable (employment), training duration and the GPS is estimated. In the third step, the DRF is estimated by averaging the conditional expectation of employment over the GPS at each level of treatment. For this paper, we use the Stata procedure "doseresponse" developed by Bia and Mattei (2008). The diagnostics from the procedure indicate that the balancing property is satisfied at the 0.01 level. The outputs from the procedure are plotted in Figure 2.

The DRF results indicate that the expectation of a successful exit to employment is highest for training durations of between approximately 3 and 18 weeks, before falling off quite steeply until the 55 to 60 week duration points. There are some indications that the probability of a successful outcome rise again for very long durations. However, the confidence intervals around these estimates are extremely wide, suggesting that no strong inferences can be drawn in this regard.

Figure 2: *Dose Response Function*



Confidence bounds at .95 per cent level
Dose response function = Probability of a positive outcome
Regression command = probit

However, as stated earlier, duration is not independent of programme type and we next examine the interaction between these two components of training. Unfortunately, due to insufficient sample sizes, it is not possible to test relationships within a DRF framework that controls for the influences of sample selection. Nevertheless, having completed our integrity checks, which suggest that the naive probit models are robust to the influences of sample selection and unobserved heterogeneity, we now return to this basic framework to examine the relationship between training type and course duration. While we are confident that our estimates are robust, the estimates should be treated as indicative given the basic nature of the estimations. To reflect the fact that training duration varies substantially between different types of training, we have distinguished between long and short duration training according to the median duration level for each category of training. The results from this analysis are presented in Table 8. The analysis suggests

Table 8: *Impacts of Training on Probability of Exiting the Live Register at 21 Months by Training Type and Duration*

	Total Sample	*Walk-ins Excluded*
Training Type:		
Job Search Training – short duration	0.259***	0.263***
	(0.066)	(0.068)
Job Search Training – long duration	–0.017	–0.014
	(0.098)	(0.112)
General Training – short duration	0.062	0.090*
	(0.045)	(0.053)
General Training – long duration	0.061	0.056
	(0.045)	(0.054)
Low-level Skills– short duration	0.114**	0.050
	(0.049)	(0.059)
Low-level Skills– long duration	0.019	–0.062
	(0.059)	(0.073)
Medium-level Skills– short duration	0.209***	0.205***
	(0.068)	(0.078)
Medium-level Skills– long duration	0.104	–0.020
	(0.071)	(0.085)
High-level Skills– short duration	0.375***	0.217
	(0.096)	(0.226)
High-level Skills– long duration	0.151*	0.212**
	(0.089)	(0.096)
	–0.011	
Observations	9,417	9,248
Pseudo R^2	0.083	0.083

that individuals participating in lower duration training programmes performed better, with the exception of high-level skills training where the results of the restricted, and arguably more robust, sample found that the longer duration high-level skills training was more effective. Given that over 90 per cent of our sample completed their training programmes at least 6 months prior to the end point of our study, we can be confident that the observed pattern of results are not driven by lock-in effects. The evidence with respect to low-level skills training was inconsistent across both samples, which raises some questions with respect to the short-term benefits of such programmes.

VI SUMMARY AND CONCLUSIONS

This paper uses a unique dataset to assess the differential impact of various types of government-sponsored training programmes and a range of training programme durations on the probability of exiting unemployment. The analysis suggests that job search training and high-level specific skills training are most likely to increase the probability of their participants exiting from unemployment. The effect of medium-level specific skills training is similar to that for higher-level skills training, although this is sensitive to the inclusion of voluntary walk-ins, which might overstate the impact of training. There is no consistent evidence to support the view that low-level skills training significantly increase the short-term labour market prospects of participants. This is consistent with the findings of previous research, which emphasises that the content of activation training should be strongly related to specific job requirements. The analysis generally supports the view that shorter duration training programmes are more effective for the unemployed, with the exception of high-level skills training where there appears to be a pay-off to more extended training duration.

These results should be considered in the light of the distribution of trainees across training programme types in our sample: only 8 per cent of trainees participated in the highly effective job search training, as did just 4 per cent in high-level specific skills training. Over two-thirds of all training days were spent in arguably much less effective low-level skill training or in general training, which we found to have only modest employment effects. Given that the educational profile of unemployed workers improved substantially following the crisis in Ireland, it would be imperative to ensure that labour market training programmes be upgraded to meet the training needs of the unemployed and match skill needs anticipated in the recovery.

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