

The role of 'culture' in apprenticeship completions

Tom Karmel
David Roberts

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About the research

The role of 'culture' in apprenticeship completions

Tom Karmel and David Roberts, National Centre for Vocational Education Research

This paper documents and finalises some work undertaken for the Apprenticeships for the 21st Century Expert Panel. It aims to explain the extent to which variation in apprenticeship completion rates can be attributed to factors relating to the 'culture' of the employer and the apprentice. Data on these types of factors are very difficult to obtain, and the authors go to considerable trouble to create two variables that reflect some aspects of 'culture'. These are the social background of the apprentice and the size of the employer. The first is based on population census data and consists of the proportion of those in trades employment in particular areas. The idea was that apprentices from areas of high trade intensity would benefit from higher levels of social support, and this support in turn is likely to be conducive to undertaking an apprenticeship. The second of these was obtained by taking one quarter's data from the National Apprentice and Trainee Collection and clerically matching employer names with apprentices to count the number of apprentices employed by each employer. The study also looked at the role of employer type (government, group training organisations and private employers).

Key messages

- Size matters: employers with at least 25 apprentices have much higher apprenticeship completion rates than smaller employers.
- Social background matters: those apprentices who live in areas where there is a greater concentration of trade employment have higher completion rates than those who live in areas with a low concentration of trade employment.
- Employer type matters: apprentices with government employers have much higher completion rates than those with private employers. Group training organisations have completion rates a little higher than private employers.

The authors point out the challenges in making use of these findings. In particular, the low apprenticeship completion rates associated with small employers are likely to be difficult to address, primarily because there are large numbers of such employers, and they employ a very large proportion of apprentices.

Tom Karmel
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Contents

Tables and figures	6
Introduction	7
Methodology	9
Results	13
Social background	13
Employer type	13
Employer size	14
The match between employer size and apprentice ‘quality’	15
The distribution of apprentices	15
Conclusions	18
References	19
Appendix A: technical details	20

Tables and figures

Tables

1	Variables used in multinomial logistic modelling	10
2	Estimated completion rates by selected characteristics and number of contracts in category	13
3	Estimated completion rates (%) by occupation and apprentice numbers, adjusted to remove employment-related effects	15
4	Apprentice distribution by employer size, by occupation (%)	16
5	Employer distribution by employer size by occupation (%)	17
A1	Model fit statistics and type III analysis of effects	22
A2	Coefficient estimates and standard errors	23
A3	Estimated completion rates (%) by occupation and apprentice numbers, with cell counts of apprentices and employers	24

Figures

1	Graph of <i>scaled size</i> against number of apprentices at employer	11
2	Completion rates for trades by number of apprentices at employer	14
3	Lorenz curve for distribution of apprentices among employers	16

Introduction

Apprenticeship completion rates have attracted much attention in recent years. As part of its remit the National Centre for Vocational Education Research (NCVER; 2010a, for example) publishes completion rates, which have been calculated on the basis of contracts of training. These estimates have hovered below 50% for some years, and their publication is often accompanied by commentary from industry stakeholders suggesting that the estimated rates don't represent what is really happening. The publication of 'individual' completion rates (Karmel 2011; NCVER 2011), which take into account apprentices moving between employers, has taken a little heat out of the argument. Nevertheless, there is no getting away from the fact that some employers have very poor apprenticeship completion rates, although undoubtedly others have high rates.

Variation in completion rates can be seen across occupations and states (see NCVER 2010a) and by the characteristics of individuals (see Ball & John 2005, for example). However, this type of statistical description is limited to the characteristics encompassed by the apprenticeship and traineeship collection and is open to the criticism that it does not take into account differences in workplaces and in the social background of apprentices.

Bardon (2010) argues that these are very important factors. He points out that there are distributions of both apprentices and employers and uses the language of 'tiers' to describe the differences across these distributions. The different tiers of apprentices are ordered by 'stickability'. The top tier consists of 'aspirational' apprentices, those who are motivated and committed to finishing their apprenticeship. Influences that Bardon mentions are a social network that includes other trade workers (through family, sports etc.) and an aptitude for the trade. The third and lowest tier is characterised by disengagement and a lack of a trade culture. Similarly, employers can be separated into 'tiers' – from large employers with a high profile, who support their apprentices well through wages and other means (tier 1), to start-up businesses, who may be motivated to use apprentices to lower wages and attract government incentives (tier 3). If there is a matching process that associates the apprentice tiers with the employer tiers, then we can expect to see very high completion rates in some parts of industry and very low completion rates in other parts. Such a mechanism is very likely because the 'best' apprentices will want to work for the 'best' employers.

The purpose of this paper is to put Bardon's general hypothesis to the test and to see whether we can quantify the variation that Bardon argues occurs among apprentices and employers. The results of this analysis first appeared in NCVER's submission to the Apprenticeships for the 21st Century Expert Panel (NCVER 2010b). The challenge is to come up with a way of operationalising these types of ideas, since we have a considerable number of background variables for apprentices, but very limited information about employers. In terms of the former we have information on age, sex, prior education, Indigenous status, whether school-based or not, whether full-time and whether an existing worker. In relation to the latter, we are limited to the sector (private, group training and government). We supplement these characteristics in two ways. First, we construct a variable from census data that is intended to capture the 'social background' factors likely to affect the level of social support that an apprentice gets. Our variable is simply the proportion of the workforce employed in the trades. Our logic is that an

apprentice coming from an area in which trades employment is common is more likely to get the social support that will encourage high completion rates. The second variable relates to employers. We construct a measure of size by counting the number of apprentices an employer has. Here our thesis is that employers with large numbers of apprentices are likely to have higher completion rates because they are more likely to have well-organised training departments and support systems. In addition, it might be expected that a large cohort of apprentices would in itself provide social support.

Having constructed these variables, we can then quantify their importance in leading to higher completion rates. We can also test whether there is a relationship between employer type and the quality of the apprentice. (We measure the latter by using a predicted completion rate for each apprentice, abstracting from the type of employer.)

In brief, we find that the social milieu of apprentices does matter in a modest way, with the completion rates of apprentices living in areas with the greatest concentration of trade workers around five percentage points higher than those who come from areas with the lowest concentration of trade workers. The size of employer turns out to be more important: completion rates for employers with more than 25 apprentices are more than ten percentage points higher than those with fewer than ten apprentices. However, there are variations across the trades, with the size of the employer mattering little in construction, for example. We also find that the highest completion rates are among government employers, with apprentice completion rates 28 percentage points higher than for private employers. Perhaps government employers have better training systems or employment conditions, and arrangements are such to discourage mobility.

We find no evidence that the larger employers are able to recruit the best apprentices. We caution, however, in making too much of this because our measure of apprentice quality is built on the level of prior education and a range of demographic characteristics – we have no measure of personal traits such as persistence or interest.

If we apply our findings to a policy solution, we can see that the most obvious way of improving average completion rates would be to restrict the employers allowed to offer apprenticeships, specifically, to impose restrictions relating to the size of employer. Such a suggestion, however, is not tenable and should not be seriously considered, for the simple reason that most apprentices are taken on by small employers. Therefore, the main policy implication to come out of this analysis is that the apprentices who are hired by employers with only a handful of apprentices will need considerable support if their completion rates are to be increased to equal those of the large employer, and this could be very expensive because of the large number of such employers.

Methodology

The natural way of determining a completion rate is by tracking a cohort of apprentices from commencement to the time when every apprentice has a result – either completion or otherwise. The time taken to complete an apprenticeship is three to four years or more, and lags in the reporting cycle can extend the time until the completion is reported to NCVET. So to track a cohort of apprentices to completion or otherwise can take up to five years, and by the time we calculate the rate it is out of date. One way of getting around this is by modelling the dynamics of the cycle and then using the resulting model to predict completion rates.

An apprentice's contract can be thought of as a finite-state process and is captured by NCVET's National Apprentice and Trainee Collection. From time period to time period the contract is one of a small number of possible states (that is, in-training, cancelled, completed) and can change from one to the other as time progresses. Moreover, there are certain states, like completion, which are absorbing; that is, an apprentice (or more accurately, a contract) cannot change from being completed to anything else. The likelihood that an apprentice will move from one state to another, such as moving from in-training to completed (or from in-training back into in-training), is called a transition probability, and this depends on how long the apprentice has been in training, as well as on background characteristics such as age and educational background (Ball & John 2005). Transition probabilities can be arranged into a matrix, one for each time period, and we can combine the probabilities to determine the probability of completion. This approach has been previously used by Mark and Karmel (2010) for vocational education and training (VET) students and by Karmel and Mlotkowski (2010) for apprentices and trainees.

The mathematical formulation of the process described above is captured by a time-dependent absorbing Markov chain (for full technical details see appendix A). We assume that there are three states in our model:

- in-training
- cancelled/withdrawn
- completed.

In the Apprentice and Trainee Collection there are more states than these (as specified in the Australian Vocational Education and Training Management Information Statistical Standard [AVETMISS]; NCVET 2008), but they have been collapsed into these three for simplicity. The biggest assumption is that contracts which have expired with no recorded outcome are counted as continuing. Ball and John (2005) assume that contracts that have expired are distributed between the states 'completed' and 'cancelled/withdrawn' in the same proportion as the rest of the contracts. What we are doing here is essentially a dynamic version of this assumption.

Now the problem arises of how to find the transition probabilities. Karmel and Mlotkowski (2010) derive the transition probabilities from the Apprentice and Trainee Collection directly. We estimate transition probabilities by running a multinomial logistic regression with three outcomes, namely in-training, cancelled/withdrawn and completed, against a range of variables, including the social background and employer size variables. Our choice of

explanatory variables necessarily includes duration and, as the likelihood of completion or cancellation/withdrawal to complete or cancel/withdraw does not have a linear relationship with duration (NCVER 2010a), we include a quadratic term for duration as well. Our ‘cultural’ variables are represented by employer size, as reflected by the number of apprentices, and social background, as reflected in the trades workers ratio and employer type. We also control for a number of background variables such as age, prior education, full-time/part-time status and so on. The choice of these variables is dependent on our dataset and draws directly on earlier exercises, notably Ball and John (2005). A full list can be seen in table 1.

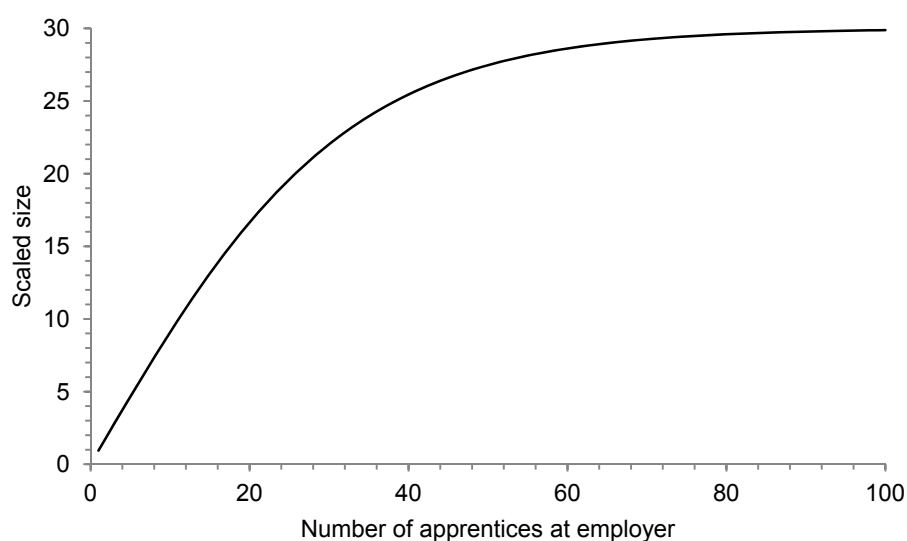
Table 1 Variables used in multinomial logistic modelling

Variable	Levels
Outcome	In-training, completed, withdrawn or contract cancelled
<i>‘Cultural’ variables</i>	
Employer size (scaled number of apprentices)	(continuous)
Social background (trades worker ratio)	(continuous)
Employer type	Private, group training, government (except defence), defence
<i>Occupation</i>	
Occupation	Engineering/ICT/science, automotive and engineering, construction, electrotechnology, food trades, skilled animal and horticultural, other trades
Occupation × employer size	As for occupation
<i>Background variables</i>	
Duration (quarters)	(continuous)
Duration squared	(continuous)
Age	(continuous)
Sex	Male, female
Prior education	Year 10 and below, senior secondary, certificate I and II, certificate III, certificate IV and above
Indigenous	Yes, no
School-based	Yes, no
Full-time	Yes, no
Existing worker	Yes, no
Qualification level	Adv. diploma, diploma, certificate IV, certificate III, certificate II

Ideally, we would use a direct measure of the size of the firm, but the data on employer size in the Apprentice and Trainee Collection is subject to data quality issues, rendering it unsuitable for this purpose. Therefore, as a proxy we measure employer size by the size of the apprentice cohort in the firm. One could argue that using the number of apprentices to measure the employer’s ‘culture’ is in fact sensible because firms with large apprentice cohorts are more likely to have training systems in place, and larger cohorts are more likely to offer peer support to the apprentices.

The employer size variable is derived in two steps. First, the number of apprentices in training is counted for each employer as at the September quarter 2007 of the National Apprentice and Trainee Collection. It is then scaled so that it increases but at a decreasing rate. The maximum value is 30, representing the average number of apprentices plus two standard deviations. The scaling factor was chosen in order to optimise the explanatory power of the model based on a common statistical measure. Appendix A contains the details.

Figure 1 Graph of *scaled size* against number of apprentices at employer



As noted in the introduction, our ‘social background’ variable measures the trade intensity of the area where the apprentice lives. It is simply the proportion of the employed population with occupations in the Australian and New Zealand Standard Classification of Occupations (ANZSCO) major group 3, and is calculated at the postcode level using data from the 2006 Census of Population and Housing.

The input data for the regression are two point-in-time ‘slices’ of the Apprentice and Trainee Collection, at the end of the September and December quarters in 2007. All those in training as at the end of the September quarter are followed through to the end of the December quarter, which is when we can ascertain whether the apprentice or trainee is still in training, has completed, or has withdrawn. Since the data collection process has lags, we are using data from as recent a time as possible that are known to be complete. Mark and Karmel (2010) use a similar method to model completion rates in the VET sector.

Once we have transition probabilities, and thus a transition matrix, we can estimate the completion rates by multiplying the transition matrix until all contracts are either completed or cancelled/withdrawn. For presentation purposes we group employers into size groups using the scaled number of apprentices variable; namely, those with one apprentice (the largest group by far) and those with 2–10, 11–25, 26–50, 51–100 and 100 or more apprentices.

To test whether there is a relationship between employer size and apprentice ‘quality’, we first need a measure of apprentice quality. We do not have an explicit measure of apprentice quality (ideally we would like to have measures of academic ability, dexterity, motivation etc.), so our approach is to equate ‘quality’ with the probability of completion, abstracting from employer characteristics or other variables that are independent of the individual. That is, we assume every apprentice: is not an existing worker; is at a private employer with 50 apprentices; and is undertaking a non-school-based certificate III full-time. We group apprentices by their occupation and the actual size of their employer and calculate the average probability of completion for each of these groups. We can then test for any relationship between an apprentice’s individual probability of completion and employer size within each occupation. A

positive relationship would be consistent with the idea that the larger employers recruit 'better quality' apprentices.

It should be noted that the variables we use relating to the individuals' characteristics are limited. They cover prior education and a series of demographic characteristics (age, sex, Indigenous status) but do not capture traits such as persistence or interest in the trade.

Results

The results of the regression modelling (described in appendix A) show that social background (as measured by the trades workers ratio) and employer size (as measured by the number of apprentices) both have a significant impact on the propensity for an apprentice to complete or not (see table A2). In addition, the coefficients for employer type show that apprentices with group training organisations, government and defence employers have a significantly higher probability of completion relative to apprentices with private employers. This means that our variables of interest have a significant impact on the likelihood of an apprentice completing their contract.

The simplest way of presenting these results is to calculate the predicted completion rates for each subpopulation corresponding to the variable of interest. The completion rates for selected characteristics, including our social background indicators, are shown in table 2.

Table 2 Estimated completion rates by selected characteristics and number of contracts in category

		Complete (%)	N
Social background (trades workers ratio)	Lowest quartile	48.0	49 510
	Middle two quartiles	50.2	97 754
	Highest quartile	52.7	47 732
Employer type	Private	49.1	160 270
	Group training	52.0	28 417
	Government (except defence)	77.6	5625
	Government (including defence)	80.3	7925
Employer size (number of apprentices)	1	46.8	50 253
	2–10	48.1	83 142
	11–25	56.9	12 973
	26–50	61.4	6825
	51–100	60.5	5089
	100 +	56.2	38 330
Total		50.4	196 612

Social background

There is an increase of about five percentage points in the likelihood of completion as the proportion of trades workers in the apprentice’s home suburb increases from the lowest to the highest quartile. This is consistent with the idea that apprentices get more social support in areas where trades employment is more common.

Employer type

The effect of employer type is large. Government-employed apprentices have a completion rate 28.5 percentage points higher than privately employed apprentices. Apprentices in the defence forces have the highest completion rates. Apprentices employed by group training organisations

have an estimated completion rate only three percentage points higher than their counterparts from individual private employers.¹

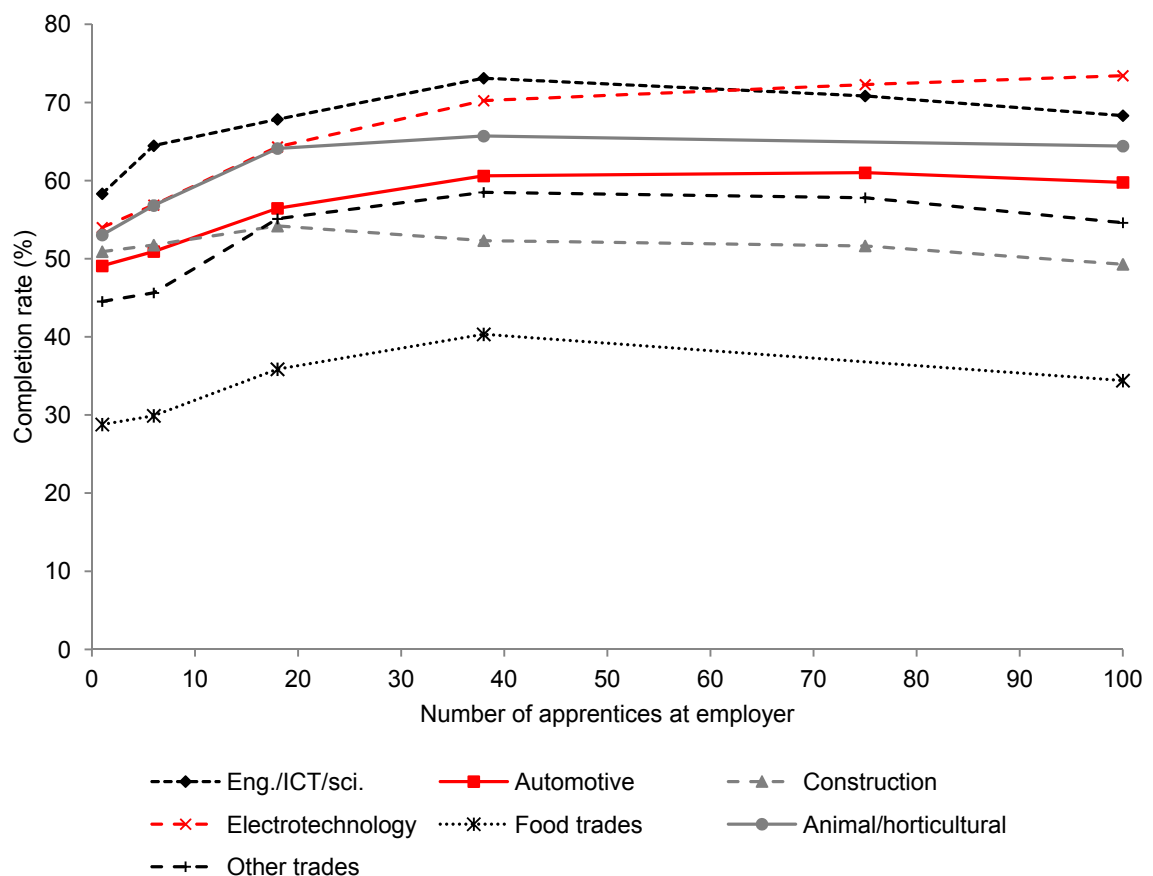
Employer size

The effect of employer size on apprenticeship completion rates is marked. The big difference occurs between employers with a small number of apprentices (say, up to ten) and those with larger numbers: those with larger numbers have much better completion rates. However, the beneficial effect of being large disappears once the employer has around 50 apprentices.

The importance of the size of the employer is even more pronounced when we control for occupation (figure 2). The numbers of apprentices and employers contributing to these estimates is given in table A3 in appendix A.

A couple of points stand out. First, with the exception of the construction trades, the number of apprentices employed within a firm affects completion rates in a very substantial way. The second is that there are decreasing returns to the size of the cohort, with no further gains in completion rates once the cohort size exceeds 50.

Figure 2 Completion rates for trades by number of apprentices at employer



¹ This may be a misestimate, though, due to some group training employers being mistakenly coded as the business where the apprentice is hosted.

The match between employer size and apprentice ‘quality’

The question of whether there is a relationship between employer size and apprentice ‘quality’ can be addressed by considering table 3, which contains completion rates adjusted to remove the effect of employment variables. That is, for every apprentice, we retain the values of the background characteristics (trades workers ratio, age, sex, prior education, Indigenous status) and duration but fix the size and sector of the employer, the type of qualification and the apprentices’ employment background (see table A4). When tabulating by employer size, we can see if larger employers have ‘better quality’ apprentices’, as reflected by their likelihood of completing.

Table 3 Estimated completion rates (%) by occupation and apprentice numbers, adjusted to remove employment-related effects

	Number of apprentices at employer					
	1	2–10	11–25	26–50	51–100	100 +
31 - Engineering, ICT and science	62.8	64.7	54.8	39.1	29.0	61.4
32 - Automotive and engineering trades	53.5	54.1	55.8	56.8	54.8	56.2
33 - Construction trades	52.1	52.4	52.8	52.4	53.0	52.8
34 - Electrotechnology and telecommunications trades	48.0	48.6	48.8	50.3	48.9	50.5
35 - Food trades	61.7	61.9	62.6	61.5	-	61.5
36 - Skilled animal and horticultural	35.3	35.3	32.3	24.7	-	33.7
39 - Other technicians and trades	55.3	54.7	57.7	57.9	57.2	56.8

Note: - means that this figure is omitted due to insufficient data.

If apprentice quality were related to employer size, then one would expect to see a trend in table 3, with the larger employers having higher adjusted completion rates than the small employers. No such trend is apparent.

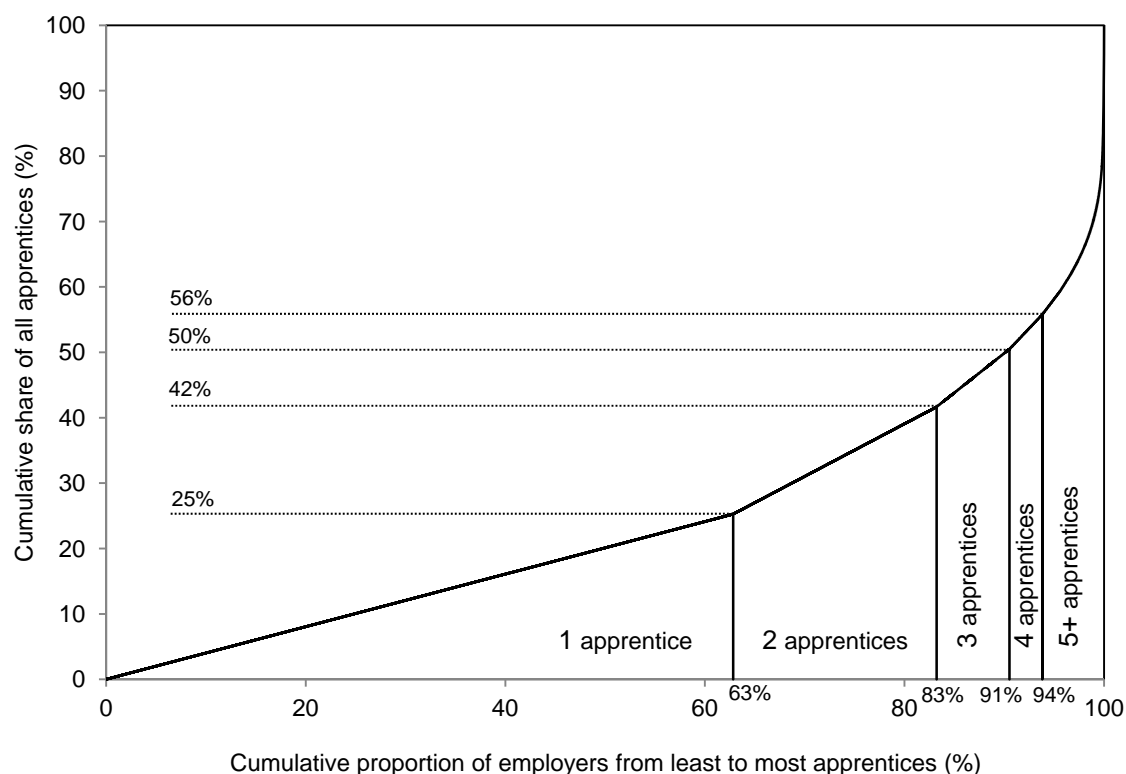
We noted earlier the caveats surrounding our measure of apprentice quality, specifically, that we have not measured personal traits such as persistence. Thus we cannot discount Bardon’s views that ‘tier 1’ employers hire ‘tier 1’ apprentices. However, we can say that we find no evidence to support his view, noting that we do have data on prior education and age, both of which could be expected to impact on apprentice quality.

The distribution of apprentices

One possible conclusion from the preceding analysis is that completion rates could be improved by preventing employers with certain characteristics from offering apprenticeships. Our calculations indicate that an obvious solution might be to restrain small employers from offering apprenticeships. However, this approach would be acceptable and only feasible if small employers accounted for a relatively small number of apprentices. We can get an idea of the distribution of apprentices among employers by drawing a ‘Lorenz curve’. To obtain this graph we rank employers by the number of apprentices they have and then plot employers against the proportion of all apprentices they employ.

We can see from figure 3 that 63% of employers have only one apprentice; that 20% of employers have two apprentices; 8% of employers have three apprentices. More importantly, employers with one apprentice account 25% of all apprentices, and employers with up to three apprentices account for 50% of apprentices.

Figure 3 Lorenz curve for distribution of apprentices among employers



We can also consider a breakdown of the Lorenz curve by occupation. This is shown in tables 4 and 5.

Table 4 Apprentice distribution by employer size, by occupation (%)

	Number of apprentices at employer					
	1	2-10	11-25	26-50	51-100	100 +
31 - Engineering, ICT and science	3	7	4	4	3	79
32 - Automotive and engineering trades	14	31	8	6	4	37
33 - Construction trades	23	32	3	3	2	37
34 - Electrotechnology and telecommunications trades	9	23	9	5	5	49
35 - Food trades	15	28	3	2	2	50
36 - Skilled animal and horticultural	8	15	4	3	3	67
39 - Other technicians and trades	14	28	4	3	3	48
All trades	25	43	6	4	2	20

Table 5 Employer distribution by employer size by occupation (%)

	Number of apprentices at employer					
	1	2–10	11–25	26–50	51–100	100+
31 - Engineering, ICT and science	54	35	4	2	1	4
32 - Automotive and engineering trades	58	38	3	< 1	1	< 1
33 - Construction trades	67	32	< 1	< 1	< 1	< 1
34 - Electrotechnology and telecommunications trades	55	40	3	1	< 1	1
35 - Food trades	60	38	1	< 1	< 1	1
36 - Skilled animal and horticultural	61	35	1	1	< 1	2
39 - Other technicians and trades	59	39	1	< 1	< 1	1
All trades	63	35	1	1	< 1	< 1

Thus, over all trades, 25% of all apprentices are employed by employers with one apprentice, and employers with one apprentice represent 63% of employers with apprentices. Similarly, 68% of all apprentices are employed by employers with ten or fewer apprentices (and 98% of employers with apprentices have ten or fewer apprentices). The concentration of apprentices in small employers occurs right across the trades, even if it is more pronounced in some than others. Any thought of constraining eligible employers by size can be rejected out of hand.

Conclusions

This study was concerned with measuring the impact of less tangible cultural variables on the completion rates of apprentices. Whereas Bardon (2010) discusses the impact of aspiration on apprentice completion rates, which is not easily measured, we have introduced some quantitative variables that capture at least part of what Bardon is talking about. Specifically, we constructed variables reflecting the social background of the apprentice (our proxy was the trade intensity of a region) and employer size (the number of apprentices employed by the firm). We also focused on employer type (private, group training, government).

All of these variables showed a statistically significant impact on completion rates. We found that the trade intensity of an apprentice's residential locality can increase the likelihood of completing by five percentage points or so when moving from the lowest to the highest quartile of trade intensity. We take this to reflect the importance of having a social background relevant to the trades. The more important factor (with the exception of the construction trades) is, however, the size of the apprentice cohort. Employers who have more than 25 apprentices have considerably higher completion rates than those with a handful. This relationship shows decreasing returns, with very large employers doing no better than those with 25–50 apprentices. Government employers have substantially higher completion rates than private employers (around 28 percentage points), while group training companies have completion rates a little better than individual private employers (around three percentage points).

We could argue from our analysis that overall completion rates would be increased substantially if small employers were to be constrained from taking on apprentices. But this is completely unrealistic (and also high-handed) because those small employers account for a very large proportion of apprentices. Therefore, it would seem that the way to improve completion rates is to modify the behaviour of small employers relative to larger employers. This is a real challenge, given the large numbers of small employers with apprentices. While it is relatively easy to hypothesise why small employers have lower completion rates than large employers, it is another matter to know what to do about it. Small employers are likely to have fewer resources and perhaps a less systematic approach to training. Government support for these employers through better case management might be a solution but is likely to be expensive, given the very large numbers of small employers with apprentices.

As for increasing the completion rates of private employers to reach those of government employers, this seems unlikely. No doubt the differences reflect the level of resources, employment conditions as well differences in priorities.

The higher completion rate of apprentices coming from areas with greater trade concentration is interesting but has no obvious implications for policy. No doubt it reflects better social support and an awareness of the trades and of trades issues, but it is not clear that this is easy to replicate.

Overall, a reasonable conclusion is that greater support for apprentices is needed if completion rates are to be improved. But the distribution of apprentices, with most undertaking their training with small employers, makes this a very expensive proposition.

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Appendix A: technical details

In this appendix, we cover some of the more technical details of the model used in this paper.

Markov chain

We model the state of a training contract as a finite-state, time-dependent absorbing Markov chain. Recall that the states are as follows:

- in-training (IT)
- cancelled/withdrawn (CW)
- completed (C).

The general transition matrix has the form

$$T(t) = \begin{bmatrix} p_{IT}(t) & p_{CW}(t) & p_C(t) \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

and we know that $p_{IT}(t) + p_{CW}(t) + p_C(t) = 1$. Here t is time measured in quarters. The probability for a contract to move from the state IT to C after N quarters is the third component of the vector $(1 \ 0 \ 0)T(1)T(2)\cdots T(N)$. We need to thus estimate the transition probabilities $p_i(t)$ and we do this by modelling these with a logistic regression.

The regression model

The multinomial logistic model is given by

$$\ln \frac{p_{IT}(t)}{p_{CW}(t)} = \alpha + \boldsymbol{\beta} \cdot \mathbf{x} + \gamma t + \delta t^2$$

(with an analogous expression for $\ln \frac{p_C(t)}{p_{CW}(t)}$) where $p_{IT}(t)$, $p_C(t)$ and $p_{CW}(t)$ are the probabilities of being in training, completed or cancelled/withdrawn, respectively, at time t ; α is the intercept, $\boldsymbol{\beta}$ is the vector of coefficients of explanatory variables (see table A.1), the vector \mathbf{x} contains the explanatory variables themselves, γ and δ are the coefficients of t and its square, and t is time measured in quarters. The quarter in which the contract commences is set to $t = 1$.

Ideally, we would use some measure of the number of apprentices relative to the size of the firm, but the data on employer size in the Apprentice and Trainee Collection is subject to data quality issues, rendering it unsuitable for this purpose. Thus the size of the firm is captured by the number of apprentices (as at the September quarter 2007).

The ‘size effect’ is expected to show decreasing returns as it increases. We have consequently transformed the simple ‘number of apprentices’ variable to reflect this.

$$scaled\ size(n) = 30 \times \left(\frac{2}{1 + \exp\left(\frac{-n}{17.5}\right)} - 1 \right) \quad (1)$$

This function has the property that as n , the number of apprentices, increases *scaled size* approaches 30 asymptotically (see figure 1). The value of 30 is chosen to be a round number

close to the mean number of apprentices plus two standard deviations, and the factor $1/17.5$ minimises the Akaike Information Criterion (Akaike 1974) in the regression models above.

Once the regression model is run, we can calculate the predicted probability for each apprentice to have each of the three outcomes, based on the variables in the model. These probabilities are used to estimate the transition matrices for a given group of apprentices at each point in time.

Once the transition probabilities are estimated, we find the cumulative completion rates. After 16 quarters the numbers become insufficient to accurately estimate transition probabilities, so we assume that transition probabilities for quarters after the sixteenth are static; that is, that we have $T(16 + t) = T(16)$, $t > 0$. To arrive at a measure of eventual completion, we take the product

$$A = T(1) \dots T(16)T(16)^{20}$$

where $T(16)^{20}$ is an approximation to $\lim_{n \rightarrow \infty} T(16)^n$, which is chosen such that the differences in entries are vanishingly small (on the order of 10^{-7}). The first row of the matrix A contains the probabilities for being in the states in-training (negligible), cancelled/withdraw and completed.

The model output

The model fit statistics are shown in table A1 and the coefficients for the multinomial regression in table A2.

Table A1 Model fit statistics and type III analysis of effects

Test	Chi square	DF	Prob chi square
Likelihood ratio	19387.1079	66	<.0001
Score	25768.723	66	<.0001
Wald	16746.9042	66	<.0001

Criterion	Intercept only	Intercept and covariates
AIC	168966.94	149711.83
SC	168987.32	150404.68
-2 Log L	168962.94	149575.83

	<i>R-square</i>	<i>Max-rescaled R-square</i>
	0.0939	0.1629

Type III analysis of effects			
Effect	DF	Wald chi square	Prob chi square
Duration (quarters)	2	73.1016	<.0001
Duration ²	2	614.4278	<.0001
Trades workers ratio	2	31.0441	<.0001
Scaled size	2	17.1984	0.0002
Age	2	256.2606	<.0001
Sex	2	153.3627	<.0001
Prior education	8	319.6254	<.0001
Indigenous	2	65.6196	<.0001
School-based	2	83.7118	<.0001
Employer type	6	158.9368	<.0001
Full-time	2	106.7229	<.0001
Existing worker	2	168.4003	<.0001
Qualification level	8	253.7218	<.0001
Occupation	12	900.9000	<.0001
Occupation × scaled size	12	153.9656	<.0001

A positive coefficient in the completion column of table A2 means that the presence of/increase in that variable increases the quarter-on-quarter likelihood for completing over cancelling/withdrawing. Conversely, a negative coefficient means that variable decreases the quarter-on-quarter likelihood for completing. The in-training coefficients can be seen as reflecting how variables affect the likelihood of continuing in a given quarter rather than cancelling/withdrawing or completing.

Table A2 Coefficient estimates and standard errors

Variable	Level	Completion		In-training	
		Coefficient	Std error	Coefficient	Std error
Intercept	-	-3.3186	0.1119	1.738	0.0724
Duration (quarters)	(cts)	0.098	0.0137	0.0786	0.0095
Duration ²	(cts)	0.0152	0.000862	0.00221	0.000697
Trades workers ratio	(cts)	0.0217	0.00425	0.0145	0.00288
Scaled size	(cts)	0.0186	0.00448	0.0101	0.00332
Age	(cts)	0.0277	0.0024	-0.00016	0.00174
Sex	Male			Reference category	
	Female	0.2238	0.0488	-0.1982	0.0326
Prior education	Year 10 and below			Reference category	
	Senior secondary	0.3144	0.0322	0.2236	0.021
	Certificate I and II	0.4474	0.0866	-0.029	0.0575
	Certificate III	0.7141	0.0611	0.1667	0.0448
	Certificate IV and above	0.396	0.0982	0.2895	0.0703
Indigenous	Yes	-0.4249	0.0907	-0.4262	0.0527
	No			Reference category	
School-based	Yes	0.4972	0.1424	-0.4274	0.0855
	No			Reference category	
Employer type	Private			Reference category	
	Group training	0.0219	0.0648	-0.1987	0.0463
	Government (ex. def)	0.7393	0.1108	0.5906	0.0935
	Defence	-0.1919	0.2596	0.7338	0.2167
Full-time	Yes			Reference category	
	No	-1.0442	0.1197	-0.0468	0.074
Existing worker	Yes	0.7172	0.056	0.327	0.042
	No			Reference category	
Qualification level	Adv. diploma	-0.817	75.7947	8.1599	60.2135
	Diploma	1.0643	0.7802	1.258	0.72
	Certificate IV	-0.282	0.1074	0.1053	0.0816
	Certificate III			Reference category	
	Certificate II	1.9091	0.1698	0.1858	0.1322
Occupation	Engineering/ICT/ sci.	1.1872	0.1368	-0.0633	0.1052
	Automotive and engineering	-0.1094	0.0671	0.0838	0.0456
	Construction	-0.0417	0.0657	0.1714	0.0446
	Electrotechnology	-0.3163	0.0812	0.233	0.0549
	Food trades	-0.3603	0.0712	-0.574	0.0436
	Skilled animal and horticultural	0.3047	0.1041	0.1052	0.0739
	Other trades			Reference category	
Occupation × scaled size	Engineering/ICT/ sci.	0.000942	0.00797	-0.00669	0.00637
	Automotive and Engineering	-0.0149	0.00507	0.00401	0.00373
	Construction	-0.0137	0.00511	-0.00824	0.00372
	Electrotechnology	-0.00214	0.00571	0.0138	0.00425
	Food trades	-0.0142	0.00582	0.00184	0.00396
	Skilled animal and horticultural	0.0134	0.00867	-0.00092	0.00683
	Other trades			Reference category	

From the regression model, each apprentice has estimated probabilities $\hat{p}_{IT}(t)$, $\hat{p}_C(t)$ and $\hat{p}_{CW}(t)$ of moving into each of the states IT, C and CW. To estimate the entries of the transition matrix $T(t)$ at time $t = 1, \dots, 16$ for a particular class of apprentices, we take all apprentices who start in time period t in that class and take the average of each of these probabilities. There are a small number of trades/employer size combinations where there aren't apprentices for every $t = 1, \dots, 16$ and so no estimates are given for these combinations.

Table A3 gives the estimates of completion rates by occupation and sample sizes used for each estimate.

Table A3 Estimated completion rates (%) by occupation and apprentice numbers, with cell counts of apprentices and employers¹

	Number of apprentices at employer					
	1	2–10	11–25	26–50	51–100	100 +
31 - Engineering, ICT and science	58.3 858 app	64.5 1336 app 557 empl	67.8* 377 app 71 empl	73.1* 320 app 30 empl	70.8** 268 app 14 empl	68.3 823 app 67 empl
32 - Automotive and engineering trades	49.1 11 648 app	50.9 22 590 app 7804 empl	56.5 5217 app 455 empl	60.6 2670 app 123 empl	61.0 1950 app 44 empl	59.8 12 255 app 96 empl
33 - Construction trades	50.9 17 642 app	51.8 22 166 app 8396 empl	54.2 1773 app 183 empl	52.3 691 app 47 empl	51.6 1067 app 24 empl	49.3 10 452 app 86 empl
34 - Electrotechnology and telecommunications trades	54.0 5762 app	56.9 11 981 app 4195 empl	64.3 2987 app 329 empl	70.2 1641 app 100 empl	72.3 1051 app 39 empl	73.4 9702 app 93 empl
35 - Food trades	28.8 5282 app	29.9 9374 app 3430 empl	35.9 780 app 69 empl	40.3 431 app 19 empl	-	34.4 3093 app 62 empl
36 - Skilled animal and horticultural	53.0 2095 app	56.8 3136 app 1172 empl	64.1 608 app 63 empl	65.7** 258 app 20 empl	-	64.4 555 app 57 empl
39 - Other technicians and trades	44.5 6966 app	45.6 12 559 app 4587 empl	55.1 1231 app 112 empl	58.5 814 app 40 empl	57.8 431 app 22 empl	54.6 1450 app 74 empl

Notes: 1 Due to the small sample sizes in some groups, estimates for some groups are either not reliable or not available (as shown by dashes and stars in the table).

Greyed entries indicate the number of app(rentices) and empl(oyers) on which that cell's estimate is based

* This figure may be up to 1% underestimated.

** This figure may be up to 3% underestimated.

- This figure is omitted due to insufficient data.

Table A4 contains the details of the variables fixed to remove employment-related effects in adjusted completion rates as shown in table 4.

Table A4 Variables fixed to estimate adjusted completion rates

Variable	Level
Employer size (scaled number of apprentices)	50 apprentices
Employer type	Private
School-based	No
Full-time	Yes
Existing worker	No
Qualification level	Certificate III



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