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Event history analysis of children in care

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Abstract
Local authorities with responsibility for social care for children should base policy on evidence of effectiveness of services they provide. This study (part of a longer term project to investigate patterns of care and impact on educational attainment in an English Borough Council) aims to (a) apply survival analysis (event history) to assess duration of care, (b) examine how such analysis can be used to support policy and planning, and (c) explore the distribution of care volume over the school years. The paper reviews previous research in this field and suggests that event history analysis (including life tables and associated analysis) appears much under-used in social care research in the UK, yet is of potential value to planners and policy makers. It is suggested that event history analysis can help to provide evidence of probable duration of care to support planning and commissioning services. Also, it is argued that the method may be considered for the analysis of national statistics on care duration.

Keywords: Event history analysis, survival analysis, children in care, care planning, commissioning

Introduction

Helping children in care to improve their educational performance is vital in enhancing their life chances, reducing their dependency on state support, and preventing social exclusion (Cabinet Office, 2006). In this context, social care planners and policy makers need evidence of what interventions have been successful (and which unsuccessful). Local authority managers often have to analyse corporate information systems about their in care populations in order to seek evidence that will inform the commissioning of services. In so doing, managers often ask an apparently straightforward question: "how long do children remain in care?". The question is deceptively simple as it seems at first it can be answered by, for instance, simply collating data on duration of care for all children and young people in care and calculating the average period. The complication is that at any time there are children still in care and we cannot know how long they will remain so (and some will have multiple care periods). A standard method known as survival analysis (often referred to as event history analysis - see Hosmer & Lemeshow, 1999) can be used to analyse data on children in care. The method includes several techniques that can be applied to analyse 'censored' data (i.e. data where the final duration of a service is unknown – as with children in care). One such technique that will be used in this paper is that which produces a 'life table' showing the probability of children experiencing a care period of specified duration.

Both the data and the application of event history analysis in this paper stem from a longer term project to evaluate the relationship between social care and educational attainment in an English local authority. The aim here, however, is to analyse duration of care and assess to what extent care periods occur during school years. Specifically, the paper will (a) produce life tables (and associated analyses) showing probable duration of care, (b) explore how such analyses can be applied to provide evidence for policy and planning, and (c) analyse the distribution of volume of care (number of days) occurring in each school year.

The method

Event history analysis focuses upon the time between two events, when some cases have not experienced the 'terminal' event when data were collected. For children in care, one could calculate the duration of episodes, or periods of care. (A care period is that time when a child is in care continuously [DFES, 2007, p.14] and consists of one or more episodes of care. An episode starts when a child enters care or when their placement or legal status changes.) The present analysis is based on care periods, since continuous care is more important in the context of educational attainment.

Event history analysis can be used to produce life tables that show the probability of remaining in care for specified periods. Like most statistical techniques, survival analysis can be used only if certain assumptions are valid. For example, Norušis (2007, p.128) notes that the conditions relevant to duration of the event in question should not change during the time span of the data analysed. For instance, for studies of employee tenure, life tables might not be appropriate if there had been a recession in the industry during the time span of the study. Definitions of the legal status of children in care (and other variables associated with their status) appear to have remained consistent enough over the time span of this study for the method to be appropriate.

The in care sample in the local authority in question was some 435 children and young people. Of these, some 84% (n=365) had one care period only. The maximum number of care periods was 11 (one client); some 9% (n=38) had two care periods; and 16% (n=70) had more than one care period. To analyse data for clients with more than one care period there are various approaches:

(i) one option is to apply event history analysis to second and later care periods by simply investigating them as though they were completely independent. The limitation of this approach is that one probably wants to assess how likely it is that an individual who has had one care period will be in care again.

(ii) methods have been developed specifically for the analysis of recurrent events (cf. Hosmer & Lemeshow, 1999, p.308). Such methods are not available in all software packages for event history analysis.

(iii) Gill (2006) outlines Markov chains, a technique for assessing the probability of transition between states, which has recently been used in research on adult social care (Pelletier *et al.*, 2005; Xie *et al.*, 2005) to analyse transitions and duration of care. Further, as Keyfitz and Caswell (2005, p.48) note, matrix methods (upon which Markov chains are based) are a logical extension of the life table (which in effect deals with two states) to multiple states. What is more, research into 'pathways' of children's social care (e.g. Schofield *et al.*, 2007, p.627) has sought to identify states, and transitions between them (though as far as one can tell, the probability of these transitions has not been calculated).

Clearly, analysis of single care periods is simpler than that of multiple periods. For the present study we restrict the analysis to a single (first) period of care as outlined later in Table Two. In the longer term it will be important to investigate methods for a more complex analysis; the option of using Markov chains seems promising since, as well as helping to analyse duration, it may extend our understanding of pathways of care.

Various software packages perform event history analysis. Tabachnick and Fidell (2001, p.829) review several, including

SPSS (version 16.0 of which was used in the present study).

Review of official statistics and previous research

It seems the only published government statistics on the topic are those relating to the duration of care for children leaving care in the relevant reporting period. DCSF (2007a) published details for 2002 to 2007, for all of England. (For instance, the published figures state that 17% of children remain in care for less than two weeks, 4% for 10 years or more, and 10% for from two up to three years).

A search of a University library database, the *British Journal of Social Work* archives, and enquiries to personal contacts, identified a few studies using event history analysis in social work. Fernandez (1999) used survival analysis to investigate duration of care in relation to restoration to biological parents and other outcomes, with children in Australia. Boyle and Willms (2001) examine multilevel models of survival analysis in the context of longitudinal studies of child development. Such models represent a development in the method that may be particularly important when investigating predictors of care duration via regression techniques. Pugh and Jones (2004) outline event history analysis methods and offer an example of how it can be applied in social work, with a study of how long children remain on the child protection register. They note that the method has not been much used in social work research in the UK.

Sinclair *et al.* (2007), as part of a wider study of permanence, include an analysis of care duration using event history analysis for a sample of 7399 children drawn from 13 English councils, with data collected in May 2003 to June 2004. They analyse duration of care in the group as a whole, in specified age bands, and by the reason for leaving care (e.g. adoption, returning home). They refer to Rowe *et al.* (1989) in their discussion of care duration, as that classic study investigated patterns of care for children in care. Rowe *et al.* presented a 'leaving care curve' (p.50) which is similar to the survival function (see below), but it is unclear whether they used event history analysis *per se* in their work.

Without an extensive literature search it is difficult to be precise on how widespread the use of the methodology is in social work research in the UK. There may be applications that have not been reported, but it seems not to be used extensively. Reported studies tend to use selected elements of the approach (and that may be quite appropriate for those applications), rather than the full range of associated methods (e.g. descriptive statistics specific to the method, survival function plots, and hazard functions – as we discuss later).

Sample data

The sample was chosen to be as large as possible, given the practical constraints of extracting and matching data from multiple databases, and to allow for reasonable sample size in analysis of subgroups. Data were gathered from an English Borough Council's data reported on the SSDA903 Statutory Return (DFES, 2007) for the three years April 1st 2004 to March 31st 2007 (chosen since full data rather than a third sample was required, as in earlier years). This data was automatically and manually checked when the return was made and in this respect was of good quality. Demographic details were included for each child, as was information on the episodes of care they received. The database for the years extracted excluded episodes that ended before April 1st 2004. Therefore, to ensure a complete history, details of earlier episodes were retrieved from corporate IT systems. The SSDA903 data consisted of 917 care episodes for 438 clients (after excluding respite cases). To pinpoint clients with these 'missing' care episodes, we identified first episodes with a reason for new episode (RNE) code other than **S** (start of care period) – 151 cases. For these 151, we retrieved episode data. Care periods were calculated for each client and those periods were numbered sequentially.

Final sample data included 1,801 care episode records for 435 clients; 566 care periods, and 435 care periods that were initial ones.

Data quality

Data quality problems often arise when collating information from multiple sources (as the literature on secondary analysis and longitudinal research acknowledges). Data quality was sought by building in internal consistency checks and by manual checking of calculated care periods and episode numbering in a sample of cases against live corporate IT systems, when episode data from the two sources were merged. For instance, checks were applied to ensure no episodes overlapped, and no episode end date pre-dated the episode start date. Such checks were automated via SPSS syntax. Even after some iteration of collation and checking there remained some anomalies and analysis had to proceed in the knowledge that one can rarely if ever have 100% correct data in this field.

We now set out in Table 1 below the demographic characteristics of the sample in regard to gender, age category and ethnicity. It can be seen that the distribution of ethnicity in males and females is similar, as is age. Overall, approximately 43% of the sample entered care when less than 5 years old, and only 6% at age 16 or older. 67% were of white ethnicity, and 20% of mixed ethnicity.

Table 1

Male

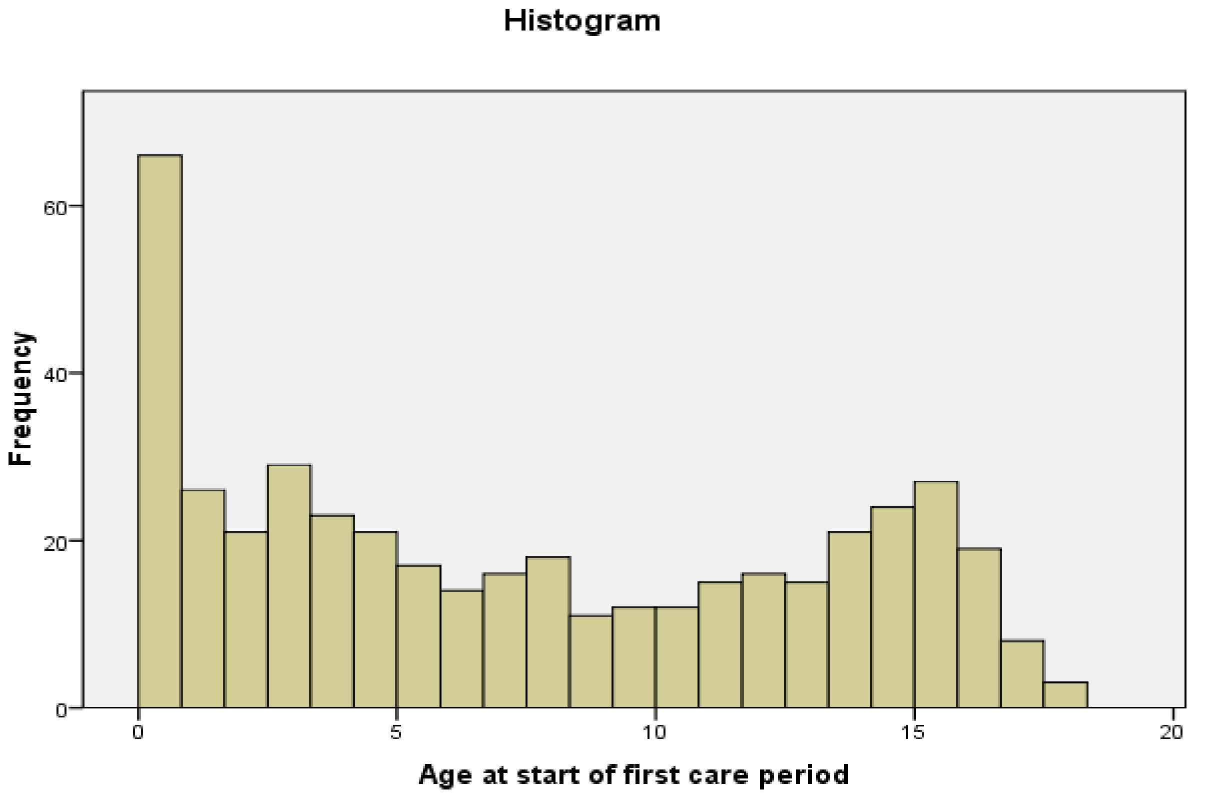
	Less than 5		5 to 9		10 to 15		16 plus		Total	
White………………	67	66.3%	33	71.7%	48	66.7%	4	33.3%	152	65.8%
Mixed………………	28	27.7%	11	23.9%	6	8.3%	0		45	19.5%
Asian or Asian British	0		2	4.3%	7	9.7%	5	41.7%	14	6.1%
Black or Black British	6	5.9%	0		10	13.9%	2	16.7%	18	7.8%
Other Ethnic Group	0		0		1	1.4%	1	8.3%	2	.9%
Total	101		46		72		12		231	

Female

	Less than 5		5 to 9		10 to 15		16 plus		Total	
White………………	55	64.7%	29	69.0%	45	71.4%	7	53.8%	136	67.0%
Mixed………………	20	23.5%	9	21.4%	11	17.5%	1	7.7%	41	20.2%
Asian or Asian British	2	2.4%	1	2.4%	2	3.2%	0		5	2.5%
Black or Black British	8	9.4%	3	7.1%	5	7.9%	4	30.8%	20	9.9%
Other Ethnic Group	0		0		0		1	7.7%	1	.5%
Total	85		42		63		13		203	

Note: Missing data resulted in one fewer case in this analysis than in the main dataset

Figure 1 Frequency distribution of age at start of first care period



When analysing the sample by age at start of first care period we can see in Figure 1 the broad frequency distribution. As can be seen, the distribution is multimodal with a peak at the youngest age (up to 1 year), then a somewhat flat distribution over other ages but with modest peaks at around 3 years and 15 years.

There are limitations to the analysis of frequency data such as these: although the distribution faithfully represents age when entering the care system, it does not, for instance, tell us anything about how long children will stay in care (and therefore their age by the time they leave care).

Analysis using life tables

A life table based on this sample is presented in Table 2. This table covers the first care period only for each case - partly because some clients have only one care period, but also because later periods may have different characteristics than the first. SPSS and other packages will produce a table with standard information. Table 2 below presents selected items from that full information and shows examples that are useful in the present context. There is guidance (e.g. Tabachnick & Fidell, 2001, p.777) that explains how values in the table are calculated (the explanation of information in the life table is adapted from Norušis, 2007, p.126).

Table 2 Life table

Interval	Number entering interval	Number still in care when data collected (censored cases)	Number leaving care	Proportion leaving care	Proportion remaining in care	Cumulative probability of remaining in care	Std. Error of cum. probability of remaining in care
Up to 1 year	435	69	143	.36	.64	.64	.02
1 up to 2 years	223	29	39	.19	.81	.52	.03
2 up to 3 years	155	23	26	.18	.82	.43	.03
3 up to 4 years	106	14	13	.13	.87	.37	.03
4 up to 5 years	79	11	11	.15	.85	.32	.03
5 up to 6 years	57	14	6	.12	.88	.28	.03
6 up to 7 years	37	4	5	.14	.86	.24	.03
7 up to 8 years	28	4	3	.12	.88	.21	.03
8 up to 9 years	21	1	3	.15	.85	.18	.03
9 up to 10 years	17	2	1	.06	.94	.17	.03
10 up to 11 years	14	2	0	.00	1.00	.17	.03
11 up to 12 years	12	0	0	.00	1.00	.17	.03
12 up to 13 years	12	3	2	.19	.81	.14	.03
13 up to 14 years	7	1	1	.15	.85	.12	.03
14 up to 15 years	5	0	3	.60	.40	.05	.03
15 up to 16 years	2	0	0	.00	1.00	.05	.03
16 and above	2	2	0	.00	1.00	.05	.03

Information in the life table is split into intervals so one can see the probability of being in care for one year, for two years, and so on. The last interval in Table 2 corresponds to 16 up to 17 years, as in England most children leave care at, or before, 18. The intervals refer to those individuals who had been in care for at least the start time of the interval. The intervals are used to read off probability values for the specified group, e.g. second row (1 up to 2 years) shows values for children who have been in care from one year up to two years.

The columns in Table 2 are interpreted as follows:

a) **Number entering interval**: number of children in care for at least the start point of the interval; all individuals (435) are counted in the first interval; second interval is a count of those who had been in care for one year or more (i.e. 223), and so on.

b) **Number still in care when data collected**: ‘censored’ cases, whose eventual duration is thus unknown:

e.g. (second row) 29 had been in care for at least one year, and were still in care.

c) **Number leaving care**: count of those who left care (e.g. of 223 children who had been in care for at least one year, 39 left care before the second year).

d) **Proportion leaving care**: the probability of leaving care (e.g. based on this sample, for those who have been in care for at least 1 year, there is a probability of ·19 of leaving care before the end of their second year).

e) **Proportion remaining in care**: the probability of remaining in care for those entering the interval: e.g. for those who have been in care for at least 1 year, there is a probability of ·81 of still being in care at the end of their second year.

f) **Cumulative proportion remaining in care**: the probability of remaining in care up to the end of the interval, for all those entering care (e.g. the probability of remaining in care for up to two years is ·52).

g) **Std. error of cumulative probability**: is an estimate of the error of the probability in the preceding column. The number of cases in later intervals is clearly rather small and so, although an error is calculated for these intervals, the probabilities should be interpreted cautiously.

Life tables can be constructed for subgroups, e.g. specified by age band, gender, ethnicity, or combinations of these factors, which can be helpful in planning (e.g. to make predictions for a group of clients). We can note that Sinclair *et al.* (2007) report probable durations of care for shorter intervals than those used here, and for durations only up to one year for their sample as a whole. However, one can compare the cumulative probability for one year, (the probability that a child entering care will remain in care for up to a year). Sinclair *et al.* (p.89) report in their sample that 54% of those entering care will still be there at the end of the year. The life table for the present sample indicates for this authority that some 64% remain in care (i.e. there is a 0·64 probability of still being in care after one year).

Through consultation with study stakeholders about the life table, it was felt that the information of most relevance to managers would be the cumulative probability of leaving care, but that this should be presented in separate tables, one for the entire sample, then one for each age group (aged up to 3 years on entering care, 3 – 6, 6 – 9, 9 – 12, 12 – 15, 15 and above). This would likely be of help in planning the commissioning of placements since, if one can identify subgroups likely to remain in care longer, one can take account of that in allocating resources. In summary, we can see that tables that offered columns giving details of the numbers entering the interval, leaving care, censored, and so on would be very useful as (i) they can be scrutinised and probed to show how the probabilities are calculated, and (ii) the absolute numbers give further information about the sample size for each interval (e.g. clearly the sample sizes for intervals at longer durations are quite small and should be interpreted with caution).

Additional analyses

Here, we discuss event history analysis in relation to other outputs, apart from life tables, that may be of use in resource planning for children in care. For example, there are techniques such as survival function plots, scatter plots of duration against other factors, and regression techniques, to identify predictors of duration. Social care applications in the UK have tended not to use these components. However, as we note below, their potential for analysis and strategic planning should not be ignored.

Scatter plots

Textbooks (e.g. Norušis, 2007, p.136) often remind us that statistical analysis should start with an examination of visual representations of the data, to help understand the distribution of variables. But, with censored data, standard methods, such as frequency histograms (e.g. Figure 1) are misleading, because they do not take account of censoring – that is, data points whose final value is not known – and, in this context, children whose final duration in care is not known (see Hosmer & Lemeshow, 1999, pp.3, 27). One solution is a scatter plot, since the plotting symbol can be used to distinguish censored and non-censored data points. Since a scatter plot displays the distribution of a variable in its relationship with a second variable, one has to select another variable of interest. In the present study, age (at start of care period) was an appropriate choice as local managers had reported anecdotal evidence of an association between the two. Figure 2 plots age against time in care. A star shows children who had left care, and empty circles censored cases (still in care when data were collected).

An unusual feature of this plot is the diagonal ceiling effect – a result of the upper limit of 18 years on children remaining in care. The plot highlights outliers (extreme scores) that may be data entry errors. In this plot there are two points with very long duration, in fact these are accurate. The scatter plot reveals a clustering at lower durations (and across ages), i.e. a concentration of cases in care for a short time. There does not seem to be a simple linear relationship between age and duration (if there were, data points would tend to cluster in a narrower cloud) and thus the plot may help in discussing with managers their anecdotal evidence of that relationship (e.g. their impression that younger children tend to remain in care for shorter periods). Of course, helpful impressions that can be gleaned from scatter plots (e.g. on the relationship of age and duration) should be tested using further statistical techniques to judge whether they are the result of chance effects.

Survival function

The survival function is a graphic representation of the life table. It is useful for comparing groups regarding care duration. For instance, the present study can be analysed to highlight gender differences in care duration. Figure 3 compares survival functions (time to leaving care) for males and females. (note that ‘survival’ in the present context refers to ‘surviving’ for a longer time in care).

The function descends very steeply over the first two years, in other words, the probability of remaining in care decreases quite markedly over this time. Also, the two functions for males and females overlap as they go up to just before the 0·6 mark, i.e. there does not seem to be a gender difference at this stage of care. It seems that the two functions are broadly parallel, in that they follow a similar path. However, the function for females, at least over the range from 2 years to just before the end, is below that for males, that is, it has a lower survival probability and thus girls are more likely to end care over that time span. The discrepancy is greatest when in care for 8 to 14 years; at 15 to 17 the two functions converge again.

Both functions tend to level out, from 10 to 15 years, in other words, the likelihood of leaving care tends to be quite constant at this stage of care.

Figure 2 Scatterplot of duration in care against age

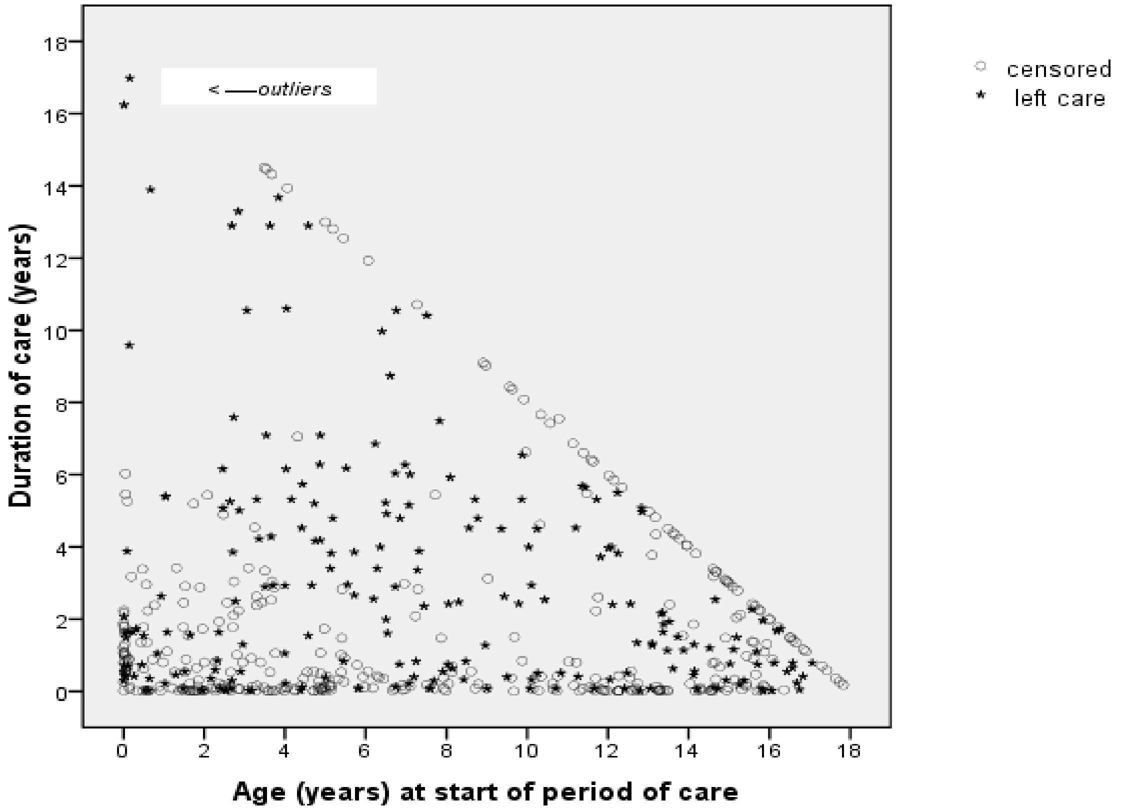
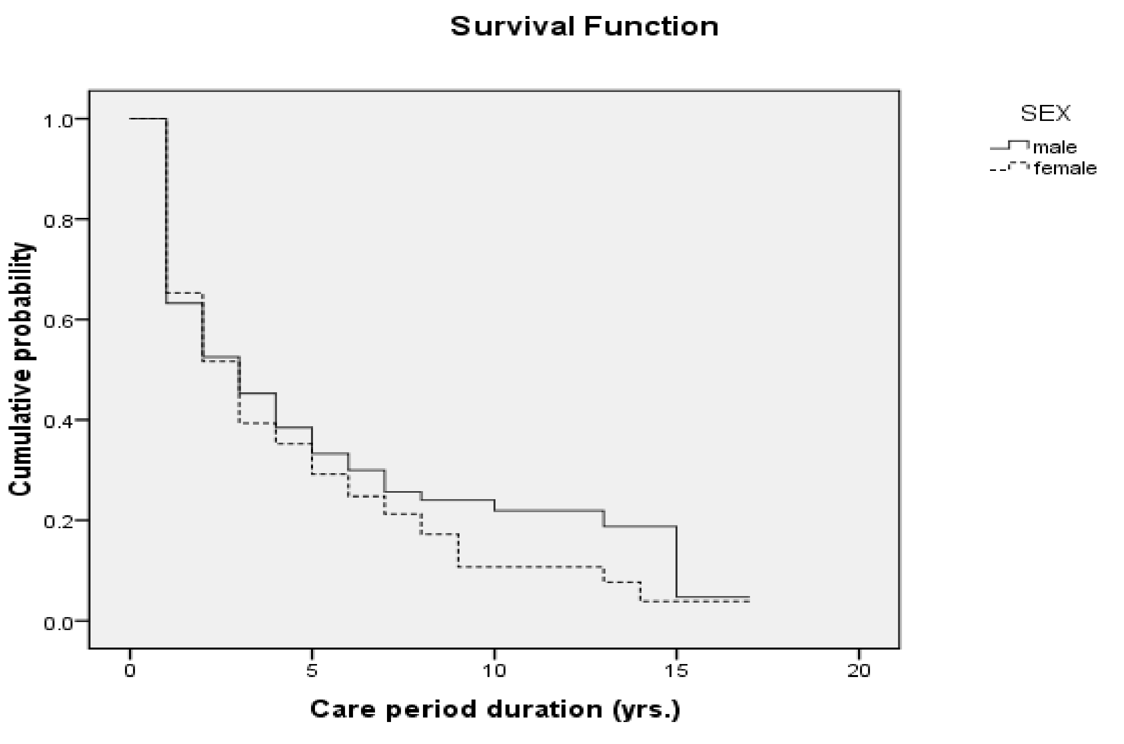


Figure 3 Survival function comparing males and females



Volume of care and school career

In evaluating which services are most effective in improving educational attainment, it is useful to analyse how care is distributed over the school years. For instance, if one knew that 80% of all care was provided in school years preceding KS1 (a school year in which the first standard attainment test is taken), services could be targeted accordingly. Therefore, it would apparently help to calculate the volume of care associated with each of the 14 school years, from *reception* (first year in the English school system) through to *year 13* (the last). Care volume is defined as the number of days in care, and reported nationally for all children in care in England (DCSF, 2007a).

Estimation of care volume per school year for each individual was based on a table of birth dates and school years. [1] For example, a child born in the year beginning 1 September 1984 (birth year 1984/1985) would have been due for school year 8 in calendar year 1997/1998 and school year 1998/1999 (there will be some error in the resulting estimates as a child may be held back or otherwise adjusted in some cases). Calculation of care volume for school years might then show, for instance, that a child born 4 May 1986 (birth year 1985/1986), and with a care period from 6 September 1996 to 1 February 1997, would receive 48 days care in school year KS2.

However, the estimates of care volume per school year would give misleading results if used to calculate distribution. For the same reason one cannot calculate duration of care – there are censored observations in each school year (i.e. for each school year there will be some children still in care, and their eventual volume for that school year is unknown). As SSDA903 data covers care only in the time up to 31 March of the reporting year, one might suppose a solution would be to edit the dataset to truncate care periods where they extend past the latest school year. This would indeed ensure that only non-censored data would be available for analysis (even if introducing complications in data collation), but it would still present a similar problem for groups of school years related to each KS test. In other words, if you wish, for example, to analyse patterns of care for the three years preceding KS3 (i.e. yr. 7, yr. 8, KS3 yr. itself), there would be censored data for the year group, even after truncation.

Instead, one could calculate life tables for each school year, for instance giving the probability that a child in care will remain in reception year for a given duration. The limitation with that is that it would not take account of the point during the school year at which care began.

To help target resources (although one cannot produce frequency distributions of care volume by school year), one can examine the number of individuals with any (non-zero) volume of care by school year. This information is summarised in Table 3. For instance, in year 3, 96 clients (29% of sample) received some care. It can be seen that the distribution is fairly uniform. This information is useful, as it suggests that care does not peak at any particular point in the school year, and so (at least on this single criterion) an implication would be (other things being equal) that resources should be evenly targeted for all school years.

Care volume is rather a crude measure of service provided, but note that the main national statutory data collection on educational attainment for children in care (the OC2, DCSF, 2007b) collects data on a care volume basis (i.e. only for children who have been in care for at least 12 months).

It is clear from this exploratory application of event history and survival analysis that more detailed measures, not just care volume, will be needed to assess how elements of service (e.g. quality of Personal

Education Plans) are related to attainment. Despite this, descriptive statistics such as those in Table 3 may help in identifying subgroups of clients for whom more detailed measures are appropriate.

Table 3

School year	Number of cases	Percent of total cases (333)
Reception	96	29%
Year 1	90	27%
KS1	90	27%
Year 3	96	29%
Year 4	87	26%
Year 5	86	26%
KS2	84	25%
Year 7	87	26%
Year 8	100	30%
KS3	99	30%
Year 10	117	35%
GCSE	115	35%
Year 12	98	29%
Year 13	71	21%

Note: Any case may count in more than one school year, therefore the number of cases does not add to the total number of cases (333)

Implications for policy and practice

Event history analysis generates valuable information for policy makers and planners. It provides data that helps answer the question: "how long do children remain in care?". This method of analysis has been in use in other domains (e.g. the life assurance industry) for many years, but apparently it has not been widely used in social care in the UK. Life tables (and associated analyses) are relatively easy to calculate using software (SPSS and other packages), and the resulting analysis should be useful for many applications in policy and planning in local authorities, where care duration is considered, and for national statistics on care duration. Consider, for example, applications in relation to annual budgets - a core task in this process is to estimate future spend for the population of children in care. The Cost Calculator for Children's Services (CCfCS: see Soper *et al.*, 2007; Soper, 2008) is an example of a software tool developed to predict cost of care over a specified period. In the CCfCS model the calculator does not allow for predictions of duration of care, rather, it assumes that the client population remains in care for the full period specified. It would therefore be useful if a prediction of duration were added to such models to enhance validity.

Sellick (2006) reports a case study of local authority commissioning of foster care from independent fostering agencies. He states that surveys show that foster care is often commissioned on a 'spot-purchase' basis (i.e. it is relatively unplanned) often resulting in budget overspend. He argues that commissioning should be planned on the basis of the needs of local authorities, in particular to cater for the volume and duration of care that can be projected.

Probability of remaining in care

The most immediately relevant information in the life table is the probability of remaining in care for a specified period. This probability applies to a client at the time they enter care for the first time. But another output from event history analysis gives the probability of remaining in care for those clients who have already been in care. For instance, children who have been in care for at least one year have in this study a probability of 81% of still being in care at the end of their second year (Table 2). This information allows planners to calculate for their population of children in care, the chance, for each individual, that they will stay in care for up to a further year (or by further calculation, for any specified period). Thus, a profile of the projected future population (and for subgroups such as those in expensive placements) can be calculated.

Care duration, care pathways and commissioning

In their review of social care commissioning, the Care Services Improvement Partnership (2008) discuss various models of commissioning (mainly in the context of adult care, but the principles apply as well to children's services). They point out that models share a "strong emphasis on … analytical thinking" (p.12). They suggest that analysis is one of four basic processes in the commissioning cycle, and identify demand forecasting and service user population profiling as elements in that process. They also observe that most local authorities have much data on service usage available but find it difficult to extract and analyse information to support commissioning. Similarly, in their handbook for managing social care budgets, the SSI/Audit Commission (2004) recommend that social care managers should analyse management information to establish the duration of clients' care, and that they should identify 'care pathways' through which clients progress. Atkinson's (2008) review of local authority children and young people's strategic plans includes an assessment of commissioning practices as embodied in these plans, and finds that most authorities did not refer to any 'model' that they used for commissioning. Whatever methods social care planners do in fact use, it seems that event history analysis would provide a useful source of information in assessing duration of care, and providing evidence for budget setting and commissioning.

National statistics on duration of care

DCSF analysis of care duration for children in care is based on clients who left care in the reporting year. Therefore, if as Sellick (2006, p.1352) suggests, children in care are tending to stay in care longer, the published figures will tend to underestimate duration in the present care population (cf. Pugh & Jones, 2004, p.908). It would be useful for policy makers if probable duration were calculated for the children in care population at a national level, and this were published instead of (or perhaps as well as) duration calculated only on care leavers.

In summary, this paper has sought to demonstrate the potential of event history analysis in research on social care for children. The discussion has, we hope, also indicated how the methods may be of benefit to policy makers and planners in relation to commissioning. Duration of care surely moderates the effect of other variables (possibly all other variables) on outcomes for children in care and, as such, is crucially important. Future development of the methods explored here is needed to examine ways of systematically applying the results of event history analysis to estimate probable cost of placements and by extension to methods of integrating cost estimation with evidence of the effectiveness of interventions in improving outcomes.

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Footnotes

[1] calculated using vector and looping functions of SPSS Command Syntax; this syntax is available on request from the author.

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