Provider Impact on Placement Outcomes

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Executive Summary

This report describes provider effects on permanency outcomes for children placed in out-of-home care. For purposes of this analysis, we measured permanency as the likelihood of exit from out-of-home care through either reunification, adoption, exit to relatives, or guardianship.

Measuring provider effects gauges whether the provider with which a child is placed influences placement outcomes. This approach isolates the effects of providers from other factors that can also influence placement outcomes such as child characteristics, placement/provider type, length of stay, and county practices.

The analysis reveals that 38 out of 202 providers had statistically significant effects on permanency. Obviously, a child's clinical differences, a county's policies and practices, and other unmeasured random factors (i.e., family environment) also have an impact on that child's likelihood of exiting out-of-home care. However, even after accounting for these measured and unmeasured factors, the analysis shows that providers are still to some extent responsible for permanency exits. Also, as a source of variation, provider variation is a larger source than county variation. Out of those 38 providers, 25 providers performed above their expected outcome and 13 providers performed below their expected outcome. All else being equal, when a given child is placed, his or her probability of exiting to permanency is affected by provider specific contributions.

Overview of the Analysis

In response to the request made by the Wisconsin Department of Children and Families (DCF), this report describes findings related to provider impact on outcomes for children placed in out-of-home care using the data provided by DCF. This research dealt with the question of whether and how many providers have an impact on child placement outcomes even after other factors that also influence placement outcomes have been controlled.

For the provider impact analysis, we examined the impact of Child Placing, Group Home, Shelter Care, and Residential Care providers. The problem at hand is common to county administered systems that rely on the private sector to provide placement services to public sector child welfare agencies. The efforts of the private providers are to some extent tied to the counties they serve. When counties work with multiple providers, how well a county manages to meet expectations set by the state is dependent on how well the private sector does its job.

To measure provider effects on placement outcomes, children placed in out-of-home care were the unit of analysis. The focus of the study was length of stay and permanency. Four permanency exits (i.e., reunification, adoptions, exit to relatives, and guardianship) were measured and used for the impact analyses.[1] The approach taken gauges whether and how many providers have an impact on placement outcomes by comparing average child outcomes achieved by a given provider to the average outcomes of similar providers given differences in the children served and placing county. Therefore, this approach separates the effects of providers from other factors (including child and county differences) that can also influence placement outcomes.

Data and Methodology

The data provided by DCF contains foster care spell records for children who were in out-of-home care from January 1, 2002 through September 30, 2013. Of particular importance, the data track entry into and out of each individual placement. Included in these data are the data needed to affiliate a placement with the provider. From these data, we constructed the complete history of individual placement moves from the first to the last placement in chronological order.

Children whose placement began in 2002 or later were included in the analyses. The records of some children were dropped from the analysis because they were placed with kin, their placement lasted only one day, their record was missing demographic data, or the data contained inconsistencies or anomalies. We also excluded those providers with less than 15 placements.

For the analysis, we were interested in whether children experienced permanency as of the censor date (9/30/2013). Questions of this sort are typically answered using some type of event history model. For this piece of the analysis, we adopted a discrete time hazard model, which is explained further in Appendix 1 of this report. Discrete time hazard models offer a number of advantages over other types of event history techniques. In the Wisconsin context, one important advantage is the fact that discrete time models are readily adapted to a multilevel problem. In order to understand the multilevel (hierarchical) problem, the relationship between child, provider, and county was considered. Children are nested within providers and also within

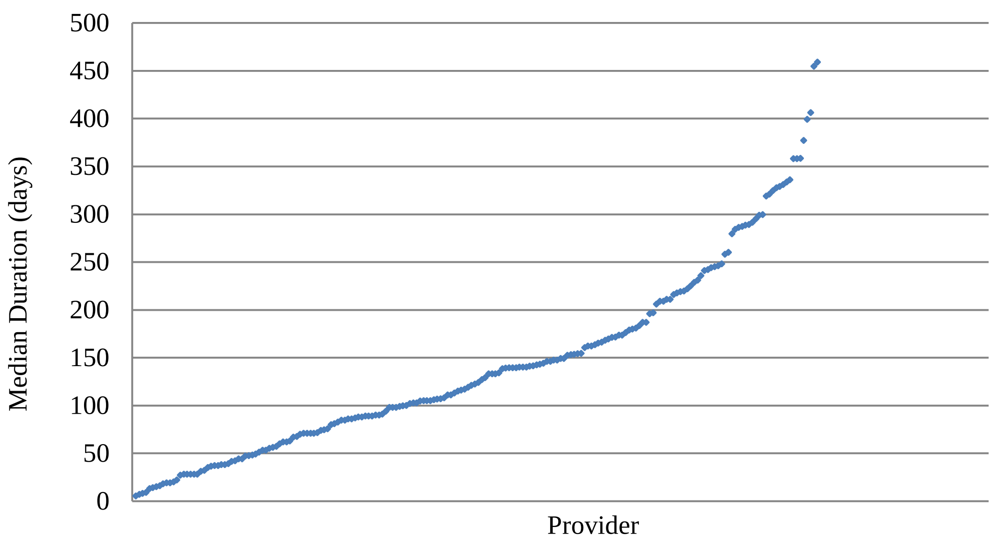
[1] After admission to placement, the child can leave placement for one of several permanency options or for one of several non-permanency options. Permanency options include reunification, adoption, exit to relatives, and guardianship, as explained. Non-permanency options include all other exit reasons including transferring to other providers, running away, and aging out.

counties, just as students are nested within schools. If a child is attached to one provider and the provider is attached to one county, we have a three-level nested (hierarchical) data structure, which is considered a typical multilevel problem. However, in Wisconsin, a provider can contract with multiple counties or one single county. To deal with this more complex multilevel data structure, a cross-classified random effects model was used. More details on a discrete time model and a cross-classified random effects mode are explained in Appendix 1.

Variation in Length of Stay and Outcomes by Provider

Figure 1and Figure 2 show the median length of stay (which is analogous to the average length of stay) and permanency rate (including reunification, adoptions, exit to relatives, and guardianship exits), respectively.

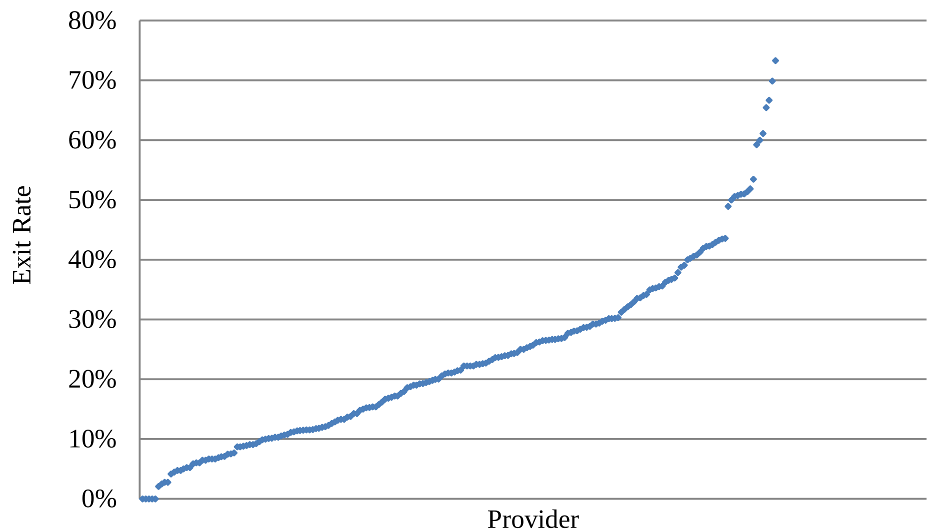
Figure 1: Median Duration in Days by Provider[2]



Among the 202 providers (having at least 15 placements), median duration and permanency exit rates vary widely. For some children, the time spent in their placement setting lasted a month or less, while others were in care for well over a year before they left their placement. Also, wide variation on permanency exit rates was also observed. The next question is whether and how much these sizable variations by provider occurred due to agency specific performance, which is presented in the following section.

[2] Two outliers that had a median duration of over 1,000 days are not included in Figure 1.

Figure 2: Rate of Permanent Exit by Provider

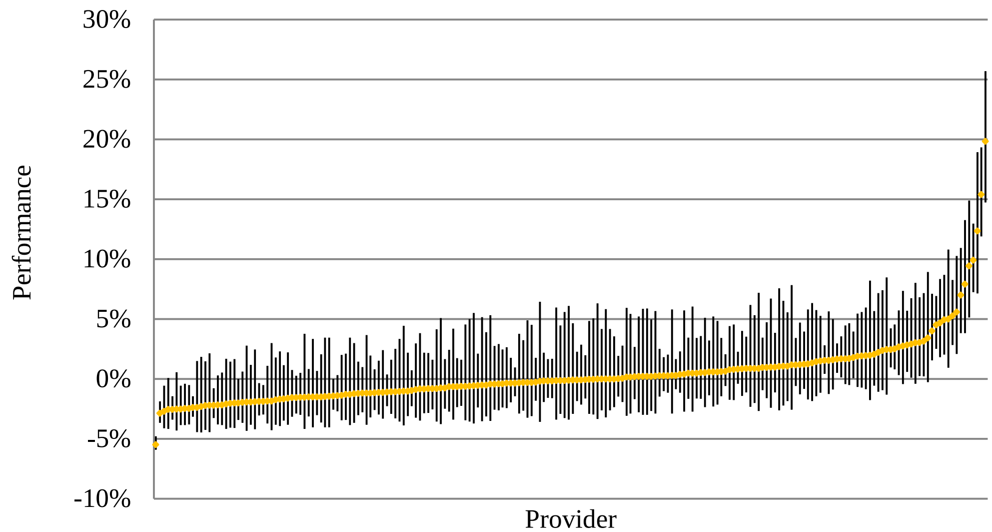


Results

As mentioned, the objective of the analysis is to ascertain whether there is a meaningful impact of providers on placement outcomes even after controlling for child effects (i.e., age, gender, race, placement type, and length of stay) and county effects. Figure 3 illustrates the ascending order of performance by provider. Each observation in the graph represents a single provider, after controlling for these other factors and the nested structure of the data. Conceptually, the results represent the difference between a provider's average permanency rate and the average rate of similar providers (the adjusted average). Because this approach separates the effects of providers from other factors that also influence placement outcomes, we can identify whether providers have an impact on the rate of permanent exits.

The vertical lines that pass through each point represent the confidence interval. The confidence interval was included here to acknowledge that there are unknown/unmeasured factors that impact placement outcomes, such as family environment. The analysis adjusts for the measured factors; the confidence interval acts as a safeguard against the influence of unmeasured factors. In cases where the vertical line passes through the y-axis at zero, the data suggest that the provider's permanency rate was not statistically different from the adjusted average. If the line does not intersect the y-axis at zero, then chances are the observed rate was indeed different from the adjusted average rate.[3]

Figure 3: Adjusted Provider Performance, Likelihood of Permanent Exit



From these data, we can conclude that, after controlling for county effects, placement type, the length of stay, and characteristics of the children, there were 38 out of 202 providers with performance that was different than the adjusted average. Therefore, even after accounting for child clinical differences, county differences, and unmeasured random factors, we can still identify 38 providers that show statistically significant effects on placement outcomes. Among the 38 providers, 25 providers had performance that was above the adjusted average; there were 13 providers that were below the adjusted average, which indicates that 25(13) providers did better (worse) than the average outcome of similar providers. Therefore, these results suggest that providers do influence permanency outcomes.

[3] The data in the Figures3 are based on multi-level models that account for the nested structure of the data (i.e., children nested within providers and counties). The data presented are the EB estimates and the associated confidence intervals. EB estimates are the level-2 residuals and measure how much the observed rate of exit differs from the statistical average.

Figure 4: Observed Provider Permanency Rate by Adjusted Performance

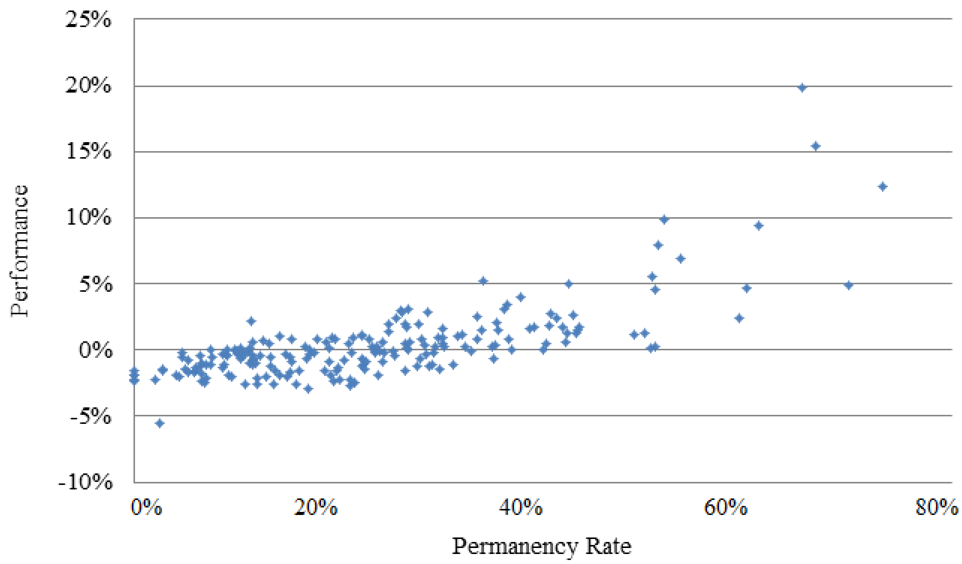


Figure 4 compares adjusted provider performance with the observed provider exit rate. These results point to the importance of using the (adjusted) performance data. Even though there is a strong correlation between the two measures, large variation was observed, especially among providers with high exit rates. For instance, among providers with exit rates of 50 percent, the adjusted performance ranged from 0 percent to 10 percent. Therefore, this comparison suggests that when evaluating placement outcomes (i.e., rates of permanent exit) one needs to consider the time spent with a provider, the admission of different child groups, and county differences, which were all reflected in the analysis.

Finally, the cross-classified random effects model separates provider variance from county variance. Table 1 shows that provider variance is larger than the county variance. Even though counties have an impact on child placement outcomes, the data indicate that, as a source of variation in the experience of children, providers have a somewhat larger impact.

Table 1: Variance Estimates

Variance Component	Estimate
Provider	0.195
County	0.153

Conclusion

This research dealt with the question of whether and how much providers have an impact on child placement outcomes even after controlling for other factors that also influence placement outcomes. We found that substantial effects on placement outcomes were observed after isolating child differences, county differences, placement type, length of stay, and random unmeasured factors. Out of 202 providers, 25 providers performed above the average of similar providers and 13 providers performed below the average of similar providers. Also, the size of provider variance was larger than the size of county variance. Therefore, the analysis shows that providers play an important role in contributing to placement outcomes.

Appendix 1: Empirical Strategy

The analysis of provider performance poses two distinct challenges: censoring and clustering/cross-classification. Censoring refers to the fact that some children do not experience the outcome of interest (permanent exit) before the observation period ends. Put another way, children whose case history is censored remain in care even though the observation window has ended. For this reason, censored observations are considered incomplete. What is known is that censored children have yet to experience the target event.

To deal with the censoring issue, special statistical models, discrete-time hazard models among them, were developed.[4] To use discrete time hazard models, the data had to be prepared in a particular way. In contrast to Cox proportional hazard models, which use one record per child, discrete time models divide (placement) time into intervals (three-month time intervals for this analysis here), with one record per interval of time through the end of observation. For a given child, there will be N records per child where N is equal to the time between events (i.e., placement and discharge) divided by the interval length plus 1.

The second problem posed by the analysis has to do with the nested/cross-classified structure of the data. In order to understand the cross-classified structure, nested structure should be understood first. Nested structures are sometimes referred to as clustered data. Children are nested within providers in much the same way that children are nested within schools. It is often the case that children within the same provider are more similar to each other than are children placed with other providers. It is also the case that the number of children in each provider differs, which means that providers differ in the amount of information they contribute to the analysis. The problem posed here is that providers are not nested exclusively within counties, even though children are nested within providers. As a result, children become nested within two different entities: providers and counties. Technically, this becomes a two level model because level 2 is the combination of providers and counties.

The cross-classified random effects model considers three main sources of variation: (1) provider variation, (2) county variation, and (3) child variation. The cross-classified discrete-time hazard model that was used appears below:

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[4] Singer, J.D & Willet, J.B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence.* Oxford University Press, 325-406.

Level 1 (child level):

$$\eta_{ijkt} = \ln(h_{ijkt} / (1- h_{ijkt})) = \Sigma T_t \text{ (Duration}_{ijkt}) + \beta X_{ijk} + \alpha_{jko}$$

Level 2 (provider level and county level):

$$\alpha_{jko} = \mu_{jo} + \mu_{ko}$$

Where μ_{jo} is the random effect for provider j and μ_{ko} is the random effect for county k.

Both are assumed to have a mean of zero and an unknown variance matrix. Each provider's and county's differences were reflected in the model by specifying both provider and county random effects. Thus, the level-2 effect is the sum of provider effects and county effects.