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# CHILD CARE QUALITY AND FOSTER CARE STABILITY:

# A TIME-TO-EVENT APPROACH

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CHILD CARE QUALITY AND FOSTER CARE STABILITY:
A TIME-TO-EVENT APPROACH

A THESIS APPROVED FOR THE
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## Abstract

Early Childcare and Education (ECE) frequently serve as the focus of efforts to improve the well-being of children in foster homes. This study uses archival data to explore the effects of ECE subsidy use, ECE type, and ECE quality on hazard models predicting foster-care disruption. We gathered data from the Oklahoma Department of Human Services (OKDHS) on foster placements, subsidized ECE use, the type of ECE (home versus childcare), and the quality of the child care (as measured by the OKDHS 'Reaching for the Stars' Quality Rating system). We fit a series of mixed-effects time-to-event models predicting foster disruption using ECE use, type, and quality. We found that ECE use decreased Hazard for all conditions, but the protective effect seemed to decrease with time. Quality Certification level did not have a uniform association with the rate of disruption, but higher qualities may last longer. Home-based care may also retain a protective effect over a longer period of time, depending on quality.

*Keywords*: Foster Care, Stability, Education, Time-to-Event.

Child Care Quality and Foster Care Stability:

A Time-to-Event Approach

## Introduction:

Foster care instability is an important issue within the child welfare system. Up to two thirds of foster children will be placed in a second foster family within two years of being placed into their first foster family (Wulczyn et al., 2002). Such instability often has severe consequences for foster children. Multiple foster care placements increase the risk of delinquency (Ryan and Testa, 2005), inhibitory control (Lewis et al 2007), and attachment disorders (Wulczyn et al., 2002). There is even evidence that multiple foster care placements worsen the effects of abuse and neglect (Rubin et al 2007). These health risks compound those that are already overabundant among foster children. Children who enter foster care are more likely to have come from backgrounds of poverty, with the attendant risks of decreased cognitive development and academic performance (Hernandez, Montana, & Clark, 2010). In short, placing foster children into multiple foster homes takes an already at-risk population, and exposes them to even more risks to their well-being.

One approach to protecting child wellbeing within the welfare system is free or reduced-tuition Early Childcare and Education (ECE). A majority of states offer increased access to ECE for foster families (Minton, Durham, & Giannarelli, 2011), and a majority of foster children are enrolled in some form of ECE (Lipscomb & Pears, 2011). Despite the massive body of research on ECE of various types on all manner of health outcomes, and its widespread use among foster families, the body of research on the interactions between ECE use and foster placement stability is relatively small

(Meloy & Phillips 2012b; Klein, Merritt & Snyder, 2016). The aim of this project is to develop this body of research by exploring some of the details regarding how ECE enrollment, type, and quality affect foster placement disruption.

*Childcare Use among foster families*

Between 55% and 59% of children in the welfare system are enrolled in some form of childcare (Ward et al, 2009). In addition to the myriad ways that ECE can benefit child development (Phillips & Lowenstein, 2011), it is entirely possible that ECE enrollment can improve the stability of foster placements. Most obviously, ECE lessens the financial burden foster families face when caring for a child, and the importance of this cannot be understated. Child care subsidies have a well-established connection to parental employment (Scott, Leymon, & Abelson, 2011). It must be said that this relationship can plausibly come from either direction; unemployment of the parent can disrupt the child's access to child care, or not having access to child care can increase the difficulty of maintaining steady employment. Regardless, subsidized ECE can help to balance the financial needs of the family with the difficulty of providing childcare (NSCAW, 2003).

Moreover, ECE may also impact placement stability through its function as a temporary relief for foster parents. In this regard, access to ECE may function similarly to respite care. This is when a foster family applies for a temporary "break" from caring for their foster child. Such support has been shown to reduce foster parents' reported stress (Owens-Kane, 2007), and increase intention to continue fostering (Rhodes, Orme, & Buehler, 2001). However, it is worth noting that respite care is often brief, and typically involves placing a child in another foster care home (U.S. Department of

Health and Human Services, 1994). By its nature, respite care necessarily increases the number of placements a foster child experiences, and the possible negative effects of numerous foster placements have already been discussed. In contrast, access to ECE may provide a similar function for parents in need of respite, can perform this function consistently over an extended period of time, and without placing a foster child in yet another foster family. This strongly suggests that ECE programs will be beneficial to the stability of foster family placements.

### *Childcare Type and Quality*

So far, the discussion has revolved around the general impact of ECE on foster-care placement stability. However, two aspects of ECE that are of special interest for this paper are the type and quality of ECE. ECE frequently comes in one of two forms: home-based or center-based care. Home-based care refers to a single care-giver operating out of their home, and caring for only a small number of children at a time. Center-based care refers to more traditional child-care centers. While there is some evidence that Center-based care is better in terms of preparing children for school (Rigby, Ryan, & Brooks-Gunn, 2007), relatively little is known about the different effects of ECE type on placement stability. Still, some compelling evidence for the differential effect of ECE type comes from literature regarding ECE and maltreatment. Child Care programs can influence foster stability by implicitly providing an extra system of supervision for the children in their care. Zhai, Waldfogel, and Brooks-Gunn (2013) found that children enrolled in the Head Start childcare program were significantly less likely to report spanking, or for their parents to be contacted by CPS in regards to the child's safety. Crucially, the significance of these protective effects depended on whether the Head Start condition was compared to parental care, pre-kindergarten, center-based, or other forms of non-parental child care. The decreased probability of CPS contact lost significance if those in the Head Start Program were compared to children in other center-based child care. The positive influence on incidence of CPS Contact and spanking both lost significance if those in the Head Start condition were compared to children in Pre-k. Given this evidence that different forms of ECE have different associations with incidence of maltreatment by family members, it follows that they may also have different effects on how long a child remains with a particular family.

Another particularly important and contentious aspect of childcare is its quality. Phillips and Lowenstein (2011) describe a division in the literature regarding the interaction of ECE quality and child development. There is a body of literature suggesting that the separation of children from their caregivers, even in the form of external childcare, can increase the incidence of behavior problems in children (Belsky et al. 2007; Loeb et al. 2007; NICHD ECCRN 2003). However, there is a competing body of literature that suggests that the quality of childcare attenuates these negative outcomes. ECE providers of low quality showed a stronger association with externalizing behavior such as aggression than did ECE providers of higher quality (McCarney et al, 2010). Higher levels of quality and quantity have both been shown to increase achievement and decrease impulsivity and risk at age 15 and similar externalizing behaviors at age 4½ (Vandell et al. 2010). This seems especially true of children from low-income backgrounds. When looking specifically at low-income children in high-quality ECE, the positive relationship between behavioral issues sometimes associated with non-maternal childcare is either absent (Loeb et al. 2004) or actually negative (Votruba-Drzal et al. 2004). The Early Head Start (EHS) Impact Study suggests that for low-income children, children enrolled in EHS showed higher levels of cognition, language, and socioemotional functioning (U.S. Dept. Health Human Services 2010b). This is particularly relevant to children in the foster system as they are more likely to have come from low-income families. Moreover, the impact on behavioral, emotional, and social development provides a possible mechanism by which ECE Quality might influence family stability. Increasing Quality may improve development, which may improve the relationship between foster child and foster parent, which may improve family stability.

Quality is also especially relevant to the State of Oklahoma. In 1998, Oklahoma implemented the Reach for the Stars program, the first Quality Improvement Rating System of its kind in the nation. This system measures child care services based on staff education, parental involvement, learning environment, and program evaluation, and assigns centers to either One-Star, One-Star Plus, Two-Star, or Three-Star categories (see Appendix A for more details on Star Category criteria). The higher the Star category, the higher the quality and the greater the tuition reimbursements. Researchers designed this program as a means of quantifying the quality of ECE providers, and of encouraging them to seek higher Star categories by improving quality. Subsequent research suggests that the Reach for the Stars program has been a qualified success; despite a lack of qualified teachers and high turnover keeping many centers from being eligible for higher Star status, the general level of Child Care quality across Oklahoma has improved. Of particular interest to this paper is the finding that, since its implementation, the number of Three-Star programs serving children in the welfare system has increased, and these programs all show greater proportions of subsidized enrollment (Norris, Dunn, Eckert, 2003). Given that the majority of children in foster care also received subsidized child-care, the Reach for the Stars program has special relevance for foster children. However, as family stability is not traditionally a primary goal of child-care or education, the literature on how programs like Reach for the Stars might impact children in foster-homes is still developing.

The possible impact ECE type and quality may have on foster placement stability is an increasingly important question. Due to a massive state budget crisis, Oklahoma considered suspending its child-care subsidy for foster children in 2016 (and low-income non-foster-care subsidies were suspended for June and July of that year). Under conditions of budgetary restraint, it is important to make informed policy decisions guided by research, and again, the research on ECE and placement stability is still young. The purpose of this study is to build on this emerging body of work, by performing a time-to-event analysis of the effect of subsidized ECE enrollment, ECE type, and ECE quality on foster-care placement disruption. Specifically, we intend to test two hypotheses:

Hypothesis 1: The hazard rates of foster care placement disruption of those who are receiving home-based ECE will be higher than those in center-based ECE.

Hypothesis 2: Higher quality ratings of ECE centers will be associated with a decrease in hazard of placement disruption for enrolled foster-children.

## Methods

### *Data*

Data have been obtained from OSDH regarding several key elements of individual children in the foster care system. Our data includes foster care placement information on 25,823 children, from 2007 to 2015.

Table 1 provides the distribution of several demographic variables of interest: age, race and ethnicity, gender demographics, and whether children were diagnosed with any kind of mental health issue.  Children ranged in age from 0 to 6 years old, with an average age at foster entry of 2.43 years. As shown in Table 2, children who received Childcare subsidies had on average 1.95 placements per child, with an average placement duration of 1.320 years; the comparison group averaged 1.40 placements per child, with an average duration of 1.01 years. Of the total sample, 15,575 (60.3%) received subsidized child care, and 10,248 (39.3%) did not. Those who did receive subsidized child care were enrolled in one (or more) of 1,130 different child care providers. Of these childcare providers, 75.7 % were Child Care Centers and 34.3% were Child Care Homes.

**Table 1**
Race/Ethnicity, Gender, and Diagnosis Condition Distribution Across Childcare Groups

| | | **Comparison Group** | **Childcare Group** | **Total** |
|---|---|---|---|---|
| **Race** | *Asian* | 38 | 35 | 73 |
| | *African-American* | 1610 | 2921 | 4531 |
| | *Native American* | 2101 | 3209 | 5310 |
| | *Pacific Islander* | 50 | 54 | 104 |
| | *Caucasian* | 6447 | 9356 | 17114 |
| | *Unknown* | 2 | 0 | 2 |
| | ***Total*** | 10248 | 15575 | 25823 |
| | | | | |
| **Gender** | *Female* | 4030 | 6100 | 10130 |
| | *Male* | 4219 | 6366 | 10585 |
| | *Unrecorded* | 1999 | 3109 | 5108 |
| | ***Total*** | 10248 | 15575 | 25823 |
| | | | | |
| **Diagnosis** | *Diagnosed* | 3501 | 6473 | 9974 |
| | *Not Diagnosed* | 6747 | 9102 | 15849 |
| | ***Total*** | 10248 | 15575 | 25823 |

Table 3 describes the frequency of ECE type and Star category. Table 3 also provides the distribution of children in each Child Care Type and Star category, but it should be noted that the sum of all children in each category exceeds the 25,823 children enrolled in Subsidized Child Care. This is due to some children being enrolled in multiple childcare sources.

*Disruption*

For this study, disruption refers to a placement ending for reasons that suggest the placement to be unstable or unhealthy for the child. Specifically, "disruption" refers to placements that end because the child requested a change of placement, because of a court order, because the child went AWOL, because the placement could not meet the child's behavioral or medical needs, allegations of abuse or neglect were brought against the provider, or if the caregiver was convicted of a crime. In addition to these, which we always consider a disruption, we coded respite as a disruption unless a non-disruptive reason was provided. For example, if a family was briefly travelling out of state, they would need to request respite care because taking a foster child across state lines is illegal. These cases were identified by a binary "NOMOVE" variable in the OKDSH placement data set. Positive "NOMOVE" values were essentially meant to

**Table 2**
Average age at first placement, number of placements, placement duration

| | **Comparison Group** | **Childcare Group** | **Total** |
|---|---|---|---|
| Age at Initial Placement* | 2.636 | 2.294 | 2.430 |
| Number of Placements | 1.392 | 1.949 | 1.728 |
| Placement Duration* | 1.014 | 1.320 | 1.215 |

*As measured in years.

**Table 3**
Distribution of Child Care Provider Type, Quality, and Enrollment of Foster Children

**Child Care Provider - Frequency**

| | | Child Care Provider Type | | |
|---|---|---|---|---|
| | | *Center* | *Home* | ***Total*** |
| **Star Rating** | *One* | 64 | 188 | 252 |
| | *One Plus* | 24 | 14 | 38 |
| | *Two* | 924 | 344 | 1268 |
| | *Three* | 225 | 26 | 251 |
| | *Unknown* | 303 | 609 | 912 |
| | ***Total*** | 1540 | 1181 | 2721 |

**Child Care Provider - Enrollment**

| | | Child Care Provider Type | | |
|---|---|---|---|---|
| | | *Center* | *Home* | ***Total*** |
| **Star Rating** | *One* | 530 | 712 | 1242 |
| | *One Plus* | 102 | 49 | 151 |
| | *Two* | 11841 | 1514 | 1335 |
| | *Three* | 6349 | 101 | 6450 |
| | *Unknown* | 4124 | 1925 | 6049 |
| | ***Total*** | 22946 | 4301 | 27247 |

Note: Grand Total of enrollment exceeds total number of children, because some children enrolled in multiple child care providers.

indicate non-disruptive, temporary placements.

*Time-to-Event Analysis*

Following the methods used in Meloy and Phillips (2012b), we fit time-to-event models to estimate the probability of foster-care disruption across time. The probability of disruption was allowed to change due to the child care conditions and demographic variables. Inclusion of time-dependent indicators of ECE use, type, and quality allowed us to also test for the significant influence of each on the hazard rate of disruption.

Specifically, we will fit time-to-event models following the form of a Cox Proportional Hazards models defined by Cox and Oaks (1984), such that

$$H(t, X) = h_0(t)e^{\sum \beta_i X_i} \tag{1}$$

where $h_0(t)$ is the baseline hazard function, which gives the probability of event occurrence given the event has not occurred prior to time t; $X_i$ refers to the value of the

$i^{th}$ covariate X, and $\beta_i$ represents the regression coefficient for $X_i$ which provides a measure of association in units of a log hazard ratio. In our case, the baseline hazard refers to the probability of a child experiencing foster care disruption, given that they have not yet experienced disruption before t days, and $X_i$ might refer to the Star Rating of that child's Childcare or Education provider. The $\beta_i$ tracks the influence of a specific covariate by representing the subject's hazard ratio such that

$$HR = e^{\sum \beta_i (X_i^* - X_i)} = \frac{e^{\sum \beta_i X_i^*}}{e^{\sum \beta_i X_i}} \tag{2}$$

where the hazard ratio represents the ratio of the hazard of an individual for whom covariate $X_i$ takes a specific value, $X_i$=$X_i^*$, divided by the hazard of an individual for whom $X_i$ takes on an alternate (typically the comparison) value, $X_i = X_i$. For purposes of examining the effects of childcare subsidy receipt, for example, $X_i$ would be a binary variable where $X_i$=$X_i^*$=1 represents a child who receives subsidized childcare, $X_i$ = 0 represents a child who does not receive subsidized childcare, and the above equation simplifies to:

$$HR = e^{\beta_i (X_i^*)} \tag{3}$$

By examining the size and significance of the hazard ratios given by the covariates in the model, as well as the measures of fit comparing models with different subsets of covariates, we can parse out the association the child care variables have with the hazard of disruption.

*Time-Dependent variables*

A complication arises due to the necessary fact that every child's use of ECE and age are going to change across the observation interval. To account for this, we set up data in a Counting Process format, with multiple rows per individual corresponding to time intervals with specific values of certain covariates (Therneau, Crowson, Atkinson, 2017). Specifically, we will use the child's current age in years, and whether the child is currently enrolled in a child-care resource as time-varying covariates. In Table 4, for example, Child 1 is placed in a foster home, begins to attend child care after 20 days, and then the placement is disrupted after another 40 days. They will have two rows of information: One with a start time *t-start* = 0 and a stop time *t-stop* = 20 days, a *childcare* variable set to 0, and a *disruption* variable set to 0, and then a second row with *t-start* = 20, *t-stop* = 60 days, *childcare* set to 1, and *disruption* set to 1. We treated *age* in a similar way. Individual 2 turns 5 years old 30 days into their placement, never receives the ECE subsidy, and their placement is disrupted. They also receive multiple rows of information. In the first, they start at *t-start* = 0, continue until *t-stop* = 30, *disruption* = 0 (because the placement hasn't actually ended at that point), and *childcare* = 0. In their second row, the time interval starts at *t-start* = 30 and continues until *t-stop* = 50, the *age* variable changes from 4 to 5, and they do experience a disruption at day 50. We accomplished this through the use of the tmerge function from the survival package, authored by Terry Therneau (2015). Gender, Race and ethnicity will be treated as constants. We will also treat whether the child ever receives a diagnosis of some mental health issue as a constant variable. The rationale here is that the term "mental

**Table 4.1**
*Example of Counting Process format of data.*

| ID | t-start | t-stop | Disruption | Child Care | Age |
|---|---|---|---|---|---|
| **1** | 0 | 20 | 0 | 0 | 4 |
| **1** | 20 | 60 | 1 | 1 | 4 |
| **2** | 0 | 30 | 0 | 0 | 4 |
| **2** | 30 | 50 | 1 | 0 | 5 |
| **2** | 50 | 60 | 1 | 0 | 5 |

health issue” covers an enormous variety of diagnoses, and OKDHS did not provide information on exact start-dates for each mental health issue of each child.

*Time-Dependent Covariates*

One foundational assumption of Cox Proportional Hazard model is the assumption that a given predictor variable has a constant influence on the baseline hazard across time. This is implicit in formula (3) in that the hazard ratio is a function only of a given predictor variable $X_i$, but contains no reference to a time variable; the hazard for an individual with $X_i = 1$ remains a constant proportion of the hazard of an individual with $X_i = 0$ across time.

However, for our last two models, we decided we wished to include an interaction with a function of time, extending formula (4) such that

$$H(t,X) = h_0(t)e^{\sum \beta_i X_i + \beta_t X_i f_i(t)} \quad (4)$$

where $X_i$ represents any particular predictor variable $X_i$, $f_i(t)$ is the function of time that corresponds to $X_i$, and $\beta_t$ represents the influence of the interaction. Let it be known that for any variable with no interaction term, $f_i(t) = 0$ and $\beta_t = 0$, and the Hazard formula simplifies to formula (1). Also let it be known that the coefficient for the main effect and the interaction term need not be equivalent; this allows us to estimate a main effect of all predictor variables, and allows that estimation to change across time for certain predictor variables.

**Table 4.2**
*Example of Gap Time Format*

| ID | t-start | t-stop | Disruption | Child Care | Age at Entry | Time Served |
|---|---|---|---|---|---|---|
| **1** | 0 | 20 | 0 | 0 | 4 | 0 |
| **1** | 0 | 40 | 1 | 1 | 4 | 20/365.25 |
| **2** | 0 | 30 | 0 | 0 | 4 | 0 |
| **2** | 0 | 20 | 1 | 0 | 4 | 30/365.25 |
| **2** | 0 | 10 | 1 | 0 | 4 | 50/365.25 |

For those models in which we include the function of time, we will also recode the data into what is often called the Gap Time format, shown in table 4.2. The noteworthy differences between this format and the counting process is the way periods of time are differences between this format and the counting process is the way periods of time are measured. Rather than tracking time continuously, each row starts at *t-start*=0, and time is measured from that starting point. Moreover, we turned the *Age* variable into *Age at Entry*, so that it indicates the age of the child at the time they began their series of placements, and stays constant across that individual's rows of data. Finally, we've added the *Time Served* variable to indicate the amount of time a given individual as accrued in their placement series prior to the current row of data, in unites of days over 365.25; this way, *Time Served* variable will be recorded in portions of a year, and a value of *Time Served* = 1 represents one year. It is this variable that we are going to use as our function of time.

*Random Effects*

Another complication arises from the fact that for purposes of this study, any given child can experience multiple placements and multiple disruption events; that is indeed the definition of foster care instability. This is why example child 2 in Table 4.1 and 4.2 has a third row of data. After they experience their first disruption event, they are put into a different foster home at Day 50 and experience Disruption again on Day 60. In instances when data is taken from the same individual multiple times, those rows of data cannot be treated as independent. To account for this, we are going to include a random effect per individual, such that

$$H(t, X) = h_0(t)e^{\sum \beta_i X_i + \beta_t X_i f_i(t) + b_i Z_i} \tag{5}$$

Where $h_0(t)$ is the baseline hazard, X and Z represents the fixed and random-effects respectively, and $\beta$ and $b$ represent the fixed and random-effects coefficients. In our case, Z represents an ID variable that is unique to each child. In this format, each child essentially has their own base-line hazard, and the coefficients $\beta$ estimate the average effect explanatory variable X has on each child relative to their own, individual baseline hazard. The influence of random-effects themselves appear in the output as a standard deviation that can be interpreted in the same way as a hazard ratio described in formula (3). Crowther et al suggest the term 'frailty' to refer specifically to the random effects in Mixed-Effects Hazard models (Crowther, Look, & Riley, 2014).

It is worth pointing out that this elaboration is not explicitly required when using all survival data. Even if an individual has multiple rows in a dataset, as with Child 1 in table 4, it would not be necessary to account for individuals contributing multiple rows. This table is merely a way of presenting the data. The likelihood function of any given model uses only one row from any one individual at any given time. However, when there are multiple events from the same individual, we must often consider including random effects (Therneau, Crowson, Atkinson, 2017).

It should also be noted that, due to the nature of mixed-effects models, inferences based on p-values are typically replaced by inferences based on Likelihood ratio tests (Winter 2013). For this reason, we will focus on comparing the fit of pairs of models as our main source of inference.

*Analysis*

The final analysis consisted of fitting a series of frailty models that predicted disruption using progressing sets of predictor variables using the 'survival' package in

R (Therneau, 2015). Model 1 will use a time-varying covariate representing subsidized ECE enrollment as its only fixed effect, and a unique frailty associated with each child ID. For Model 2, we will divide the single ECE variable into two variables based on ECE type: one for Center-based ECE and one for Home-Based ECE. By looking at the different regression coefficients and the different hazard ratios, we can see how the two different ECE types affect the hazard of disruption.

Model 3 will have the same frailty term, but will divide the ECE-use variable into 4 dummy variables representing ECE resources of each of four Star categories: 1 Star, 1 Star Plus to 2 Star, 3 Star, and Unknown. We made the decision to collapse the ECE providers of 1-Star Plus and 2-Star designations into a single group for two reasons. First, the distinction between 1-Plus and 2-Star criteria is more ambiguous than those between other categories. The 2-Star criteria involve meeting all of the 1-Star Plus criteria plus one of two requirements: either meeting a set of additional criteria OR receiving accreditation from some other national accrediting body approved by child services. However, the current dataset does not include information about which set of criteria an ECE provider met to achieve 2-Star status; all that is certain is that a 2-Star ECE provider must have at least met 1-Star Plus criteria and some additional quality criteria. In contrast, a 1-Star designation only involves being licensed to operate for 6 months. For these reasons, the 1-Star Plus designation was considered more similar to the 2-Star category than to the 1-Star. Moreover, the 1-Star Plus category is the smallest, including fewer providers and fewer foster children then all other categories. For the above reasons, the 1-Star Plus and 2-Star designations were grouped together. For the purposes of this study, the Star designations were renamed Low Quality (1-

Star), Medium Quality (1-Star Plus and 2-Star), and High Quality (3-Star). A log-likelihood ratio test comparing the model using these three levels of quality with a model including all four Star categories showed no significant difference in fit, $X^2(1) = 0.87$, p=0.35. This suggests no strong statistical justification to separate 1-Star Plus and 2-Star ECE providers.

We also made the decision to treat those ECE resources of unknown Star category as their own category, rather than lump them in with 1-Star (which by default includes all ECE resources licensed to operate), so as to get a more unambiguous estimate of the impact of 1-Star ECE programs on disruption.

Model 4 has 8 fixed predictor variables, representing the interaction between ECE type (Home versus Center-based care) and each of the 4 quality ratings, giving more detail on these two aspects of child care. Model 5 includes all of the above, plus a series of demographic variables. These are added in at the end in order to see how their inclusion changes the estimation of the most granular ECE type and quality variables.

Finally, we decided to run Models 6 and 7, which are identical to models 4 and 5 respectively, except that we have allowed the ECE-based predictor variables to have an interaction with a function of time. This function of time will simply the *Time-Served* variable as shown in table 4.2. Of note is that, during preliminary analyses, we found that *Time-Served* was a more significant measurement of time than the raw age of the child, and even more significant than an indicator of the number of prior disruptions.

## Results

First, we will fit two similar models to parse out the main effects of ECE receipt and ECE type. Model 1 contains only a single variable, where ECE = 1 represents a

**Table 5:**
Preliminary Hazard Models

| | Variable | β | se | HR (95% CI) |
|---|---|---|---|---|
| **Model 1** | ECE | -0.03 | 0.02 | 0.97 (0.93 – 1.01) |
| | | | | |
| **Model 2** | Center | -0.01 | 0.021 | 0.988 (0.947 – 1.016) |
| | Home | -0.17*** | 0.042 | 0.843 (0.776 - 0.915) |

*Model 1 – Unique frailty per client ID: sd=0.96, HR=2.62*
*Model 2 – Unique frailty per client ID: sd=0.96, HR=2.62*
*$*p < .05$. $**p < .01$. $***p < .001$.*

child who receives subsidized ECE, and ECE = 0 represents a child who does not. The results are given in table 5. The regression coefficient, β = -0.035 gives a hazard ratio of 0.965, approximately 96.5% of the hazard we would expect of those who are not receiving ECE, suggesting that the receipt of subsidized childcare slightly decreases the hazard of disruption. The standard deviation of the frailty effects in Model 1 is 0.963, giving a sense of the distribution of the individual frailties. A useful property of this measure is that it can also be exponentiated and interpreted like a hazard ratio. Thus, an individual with a unique frailty one standard deviation above the mean can be interpreted as having a HR = exp(0.963) = 2.619, or having 161.9% increased hazard for that individual. This suggest a very high amount of variance between individuals in this dataset. This finding mostly persists across models. In Model 5 the variance of random effects on the baseline hazard are only slightly decreased, with individuals one standard deviation above the mean baseline hazard showing a hazard ratio of HR=2.323.

Delving more deeply, we fit Model 2, which contains two fixed binary variables indicating whether a child is receiving Center-based ECE or Home-based ECE. The fixed coefficient of Center-based ECE receipt is β = -0.012, p > 0.57. Thus, those who receive Center-based ECE have a hazard ratio of 0.988, suggesting that children in

**Table 6**
*Model 3: parsing regression coefficients and Hazard Ratios for each Quality Rating of ECE*

**Model 3**

| Variable Name | β | se | HR (95% CI) |
|---|---|---|---|
| LOW | -0.19* | 0.08 | 0.83 (0.71 – 0.96) |
| MED | -0.01 | 0.03 | 0.99 (0.94 – 1.04) |
| HI | -0.09** | 0.03 | 0.91 (0.85 – 0.98) |
| Unknown | -0.01 | 0.03 | 0.99 (0.93 – 1.06) |

*Unique frailty per Client ID: sd=0.96, HR=2.62*
*$*p < 0.05$ $**p < 0.01$ $***p < 0.001$*

Center-based ECE has a hazard that is 98.8 percent of the hazard of those who receive no type of ECE. Those in the home-based care, however, fare much better, with a hazard ratio of 0.843, or only 84.3% of the hazard of those receiving no type of childcare, $\beta = -0.171$, $p < 0.001$. Moreover, a log-likelihood ratio test suggests that Model 2 represents a significant improvement in fit over model 1, $X^2(1) = 14.967$, $p < 0.001$. Overall, this suggests that ECE as a whole has a modestly negative effect on disruption, that allowing the estimation of two different hazard ratios for the two different types of child care is associated with a significant improvement in model fit, that Home-based ECE has a significant, negative relationship to disruption, while Center-Based ECE has a negligible association with disruption. Table 6 displays the results of Model 3. Here, each quality rating is given its own dummy variable; each categorical variable equals either 0 or 1, based on the quality of the ECE provider, and for individuals who do not receive subsidized ECE, each category variable equals zero. It is worth reiterating that Model 3 makes no distinction between Center-based and Home-based care. Those ECE providers with a Low-Quality rating have a significantly negative regression coefficient of $\beta = -0.191$, yielding a hazard ratio of 0.826. This suggests that foster families with children enrolled in a Low-Quality ECE resource have only 82.6% of the disruption hazard of those who are not receiving any kind of ECE.

However, increasing the quality of the ECE as measured by Star rating does not uniformly decrease the hazard of disruption. Those enrolled in Medium-Quality ECE show hazard ratio of 0.991, suggesting that enrollment in this category of ECE has no association with disruption hazard, β = - 0.009, p=0.72. Children in High-Quality ECE programs have only 91.2% of the hazard of those who do not receive subsidized ECE, β = -0.092, $p < 0.01$. This suggests an improvement, but oddly is not as large an improvement as estimated for a Low-Quality program. Enrollment in an ECE provider with no record of quality as measured by the Reach for the Stars Program shows no significant change in the hazard of disruption, β=0.007, p = 0.830. Also of note is the fact that dividing ECE-enrollment up by Quality-Rating showed a significant improvement in fit over Model 1, $X^2(3) = 11.383$, $p < 0.01$.

Table 7 shows a side-by-side comparison of the results of Models 4 and 5. Model 4 contains 8 binary variables specifying enrollment in one of 8 ECE conditions (2 ECE Type categories x 4 ECE Quality categories). The "C" and "H" in the variable names correspond to "Center-based ECE" and "Home-based ECE" respectively. Table 7 shows that the relation of ECE quality to stability varies markedly across ECE type. The hazard ratio for Low Quality Center-based ECE is HR = 0.92, β = -0.084, p = 0.46, where Low Quality, Home-based ECE has a hazard of HR = 0.765, β = -0.207, $p < 0.01$. This suggests that ECE of the lowest quality is helpful in both cases, but only significantly helpful in the case of Home-based care, which outperforms Center-based Low Quality providers. In the Medium range of quality, there is an even more pronounced difference. The hazard ratio for Medium Quality Home-based ECE is HR = 0.714, β = -0.337, $p < 0.001$; for Medium-Quality Center-Based ECE, the hazard ratio is

HR = 1.027, β = 0.027, p = 0.30. In the Medium Quality category, Home-Based care reduces the hazard significantly, while Center-based shows a small increase in hazard of disruption. This is made even more noteworthy by the fact that a sizeable majority of ECE programs are rated of Medium Quality. This also gives more detail in regards to Model 2. Model 2 shows that center-based ECE enrollment, when taking all quality levels together as a whole, shows little relation to Disruption. Model 4 shows us that this is likely due to the Middle-Quality Center-Based Category being both the least reductive of the hazard and the most common quality rating. In the High-Quality category, Center- Based ECE shows a significant decrease in the Hazard Ratio, HR = 0.913, β = -0.091, p < 0.01. While not significant, High-Quality Home-Based ECE also decreases the hazard of disruption, HR = 0.844, β = -0.169, p = 0.49. Interestingly, the High-Quality Center- Based ECE enrollment does indeed have the greatest decrease in hazard of disruption among the Center-Based options. In contrast, among the Home-Based categories, enrollment in the highest quality category underperforms Low and Medium-Quality. For both Home-based and Center-Based categories, having no quality rating is associated with an insignificant change in hazard. Model 4 shows a significant improvement in fit over model 3, $X^2(4) = 30.469$, p < 0.001.

In comparison, Model 5 includes all the Quality-by-Type variables in Model 4, but includes a number of demographic variables shown to be relevant in prior studies. The Age variable is unique in that it is set up to take multiple values, from 0 to 6. As each client is given a new row suggesting a new time interval, in which all other variables are kept the same but the Age variable increments by one year. The Age variable suggests that for each year of age, the hazard of disruption increases by an

**Table 7**

*Model 4 & 5: Modeling Type and Quality, and Type and Quality and Demographic variables*

| | **Model 4** | | | **Model 5** | | |
|---|---|---|---|---|---|---|
| Variable Name | β | se | HR (95% CI) | β | se | HR (95% CI) |
| C: LOW | -0.08 | 0.11 | 0.92 (0.74 – 1.15) | -0.09 | 0.11 | 0.91 (0.73 - 1.13) |
| C: MED | 0.03 | 0.03 | 1.03 (0.98 – 1.08) | 0.04 | 0.03 | 1.04 (0.99 - 1.09) |
| C: HIGH | -0.09** | 0.03 | 0.91 (0.85 – 0.98) | -0.08* | 0.03 | 0.92 (0.86 – 0.99) |
| C: Unknown | -0.01 | 0.04 | 0.10 (0.92 – 1.08) | -0.01 | 0.04 | 0.99 (0.92 – 1.07) |
| H: LOW | -0.27** | 0.10 | 0.77 (0.63 – 0.93) | -0.19 | 0.10 | 0.83 (0.67 – 1.00) |
| H: MED | -0.34*** | 0.07 | 0.71 (0.62 – 0.82) | -0.30*** | 0.07 | 0.74 (0.65 – 0.85) |
| H: HI | -0.17 | 0.25 | 0.84 (0.52 – 1.37) | -0.08 | 0.24 | 0.92 (0.58 – 1.48) |
| H: Unknown | -0.01 | 0.06 | 0.99 (0.88 – 1.11) | 0.03 | 0.06 | 1.03 (0.92 – 1.15) |
| Diagnosis | | | | 0.25*** | 0.02 | 1.28 (1.23 – 1.34) |
| Age | | | | 0.14*** | 0.01 | 1.15 (1.14 – 1.16) |
| Hispanic | | | | 0.04 | 0.03 | 1.04 (0.98 - 1.10) |
| African-American | | | | -0.05 | 0.03 | 0.95 (0.90 - 1.01) |
| Native American | | | | 0.02 | 0.02 | 1.02 (0.98 – 1.07) |
| Male | | | | 0.10*** | 0.02 | 1.10 (1.05 – 1.15) |
| Sex NA | | | | -0.02 | 0.03 | 0.99 (0.93 – 1.04) |

*Model 4 – Unique Frailty per Client ID: sd=0.96, HR=2.62*
*Model 5 – Unique Frailty per Client ID: sd=0.84, HR=2.32*
**p < .05. **p < .01. ***p < .001.*

average of 15%, β = 0.140, p < 0.001. Children diagnosed with any kind of health care issue have approximately 28.4% of the hazard of disruption of children without a diagnosis. For purposes of examining the effect of race and ethnicity, we included several binary dummy race variables, with Caucasian being the reference group as they were the most commonly-occurring ethnicity. Being African American shows a small protective effect relative to the reference group, with a hazard ratio of 0.954, β = -0.047, p = 0.11. The ‘Hispanic’ and ‘Native American’ status variables did not significantly affect the risk of disruption. The gender of the child comes in the form of two dummy variables, one *Male* binary variable identifying male children and one *Sex-NA* binary variable identifying cases of missing data. In this way, we can distinguish between known males, known females, and those with missing data, with female children being the reference group. Males were more at risk of disruption than females, with a hazard ratio of 1.102, $\beta = 0.097$, $p < 0.001$. A likelihood ratio test comparing models 4 and 5 shows that Model 5 represents a significant improvement in fit, $X^2(7)=737.13$, $p<0.001$. The inclusion of these demographic variables also alters the estimates of the coefficients associated with ECE and Quality. The Medium-Quality Center-Based variable is associated with an increased risk in hazard, HR = 1.039, $\beta = 0.039$ $p = 0.13$. Medium-Quality Home-Based ECE remains associated with a significantly decreased risk, HR = 0.745, $\beta = -0.295$ $p<0.001$. Low-Quality ECE of both Center-Based and Home-Based categories retain their negative effect on the hazard. The same is true of the High-Quality ECE, though only the High-Quality Center-based ECE reaches significance, $\beta = -0.079$, $p < 0.05$. The coefficient for High-Quality Home-Based ECE retains a sizeable effect size of HR=0.919, but fails to reach significance, $\beta = -0.084$, $p = 0.73$. Also of note is that missing quality ratings are apparently missing at random with respect to our included covariates, as they never reach significance in any model. The largest change in hazard associated with a missing quality rating is in Model 5, at HR = 1.026, $\beta = 0.026$ $p = 0.66$. This suggests that, with respect to our observed covariates, their likely is nothing systematic about the missingness within ECE Quality ratings.

The final two models involve the interaction with the *Time Served* variable, and so have been run on the Gap Time formatted data. It is worth repeating that we chose *Time Served* as a function time because, during early analyses, it seemed to overshadow the age or even prior number of disruption events experienced by the child. Model 6 is identical model 4, except for the inclusion of the *Time Served* variable, its interaction

**Table 8**
*Model 6 & 7: Modeling Type and Quality, and Type and Quality and Demographic variables*

| Variable Name | Model 6 β | Se | HR | (95% CI) | | Model 7 β | se | HR | (95% CI) | |
|---|---|---|---|---|---|---|---|---|---|---|
| C: LOW | -0.69*** | 0.15 | 0.50 | (0.37 | 0.67) | -0.7*** | 0.15 | 0.50 | (0.37 | 0.67) |
| C: MED | -0.41*** | 0.03 | 0.66 | (0.63 | 0.70) | -0.41*** | 0.03 | 0.66 | (0.63 | 0.70) |
| C: HIGH | -0.56*** | 0.04 | 0.57 | (0.53 | 0.61) | -0.56*** | 0.04 | 0.57 | (0.52 | 0.61) |
| C: NA | -0.38*** | 0.05 | 0.68 | (0.62 | 0.75) | -0.39*** | 0.05 | 0.68 | (0.61 | 0.75) |
| H: LOW | -0.7*** | 0.13 | 0.50 | (0.38 | 0.64) | -0.68*** | 0.13 | 0.51 | (0.39 | 0.65) |
| H: MED | -0.7*** | 0.09 | 0.50 | (0.42 | 0.59) | -0.69*** | 0.09 | 0.50 | (0.42 | 0.60) |
| H: HI | -0.48 | 0.32 | 0.62 | (0.33 | 1.16) | -0.52 | 0.32 | 0.59 | (0.32 | 1.11) |
| H: NA | -0.41*** | 0.08 | 0.66 | (0.57 | 0.78) | -0.40*** | 0.08 | 0.67 | (0.57 | 0.78) |
| Time Served | -0.96*** | 0.03 | 0.38 | (0.36 | 0.41) | -0.97*** | 0.03 | 0.38 | (0.36 | 0.40) |
| C: LOW*T | 0.68*** | 0.14 | 1.97 | (1.50 | 2.60) | 0.68*** | 0.14 | 1.97 | (1.50 | 2.60) |
| C: MED*T | 0.44*** | 0.04 | 1.55 | (1.44 | 1.68) | 0.44*** | 0.04 | 1.55 | (1.44 | 1.68) |
| C: HI*T | 0.46*** | 0.05 | 1.58 | (1.44 | 1.75) | 0.46*** | 0.05 | 1.58 | (1.44 | 1.75) |
| C: NA*T | 0.31*** | 0.07 | 1.36 | (1.19 | 1.56) | 0.32*** | 0.07 | 1.38 | (1.20 | 1.58) |
| H: LOW*T | 0.54*** | 0.14 | 1.72 | (1.30 | 2.26) | 0.54*** | 0.14 | 1.72 | (1.30 | 2.26) |
| H: MED*T | 0.37*** | 0.11 | 1.45 | (1.17 | 1.80) | 0.37*** | 0.11 | 1.45 | (1.17 | 1.80) |
| H: HI*T | 0.39 | 0.36 | 1.48 | (0.73 | 2.99) | 0.41 | 0.36 | 1.51 | (0.74 | 3.05) |
| H: NA*T | 0.36*** | 0.09 | 1.43 | (1.20 | 1.71) | 0.37*** | 0.09 | 1.45 | (1.21 | 1.73) |
| Age at Entry | 0.14*** | 0.01 | 1.15 | (1.13 | 1.17) | 0.14*** | 0.01 | 1.15 | (1.13 | 1.17) |
| Diagnosis | | | | | | 0.24*** | 0.01 | 1.27 | (1.25 | 1.30) |
| Hispanic | | | | | | 0.03 | 0.03 | 1.03 | (0.97 | 1.09) |
| African-American | | | | | | -0.05 | 0.03 | 0.95 | (0.90 | 1.01) |
| Native American | | | | | | 0.02 | 0.02 | 1.02 | (0.98 | 1.06) |
| Male | | | | | | 0.09*** | 0.02 | 1.09 | (1.05 | 1.14) |
| Sex NA | | | | | | -0.04 | 0.03 | 0.96 | (0.91 | 1.02) |

*Model 6 – Unique Frailty per Client ID: sd=0.80, HR=2.23*
*Model 7 – Unique Frailty per Client ID: sd=0.79, HR=2.20*
**p < .05. **p < .01. ***p < .001.*

with the ECE variables, and the *Age* variable has become the *Age at Entry* variable. In model 6, we see a fairly different story than in Model 4. Most immediately, the main effects of ECE at all levels of quality are significantly negative, suggesting a notable reduction in the rate of disruption for all Quality and Type categories. This is even true of Center-based Medium Quality, HR = 0.66, β = -0.41, p < 0.001. This is at odds with prior models. However, the interaction of the Center-based Medium-Quality variable and the continuous *Time Served* variable shows a positive influence on the rate of disruption occurrence, HR = 1.55, β = 0.44 p < 0.001. This might explain why Center-based Medium care was showing no protective effect on average in Model 4. It may not have a protective effect when averaged across time, but it does seem beneficial until the *Time-Served* variable reaches approximately 1 year. Center-based High-Quality care shows mostly the same pattern, with a significant main effect, $\beta = -0.56$ $p < 0.001$, with an interaction of time, $\beta = 0.46$ $p < 0.001$. This may indicate that it will take more than a year for main effect to be cancelled out by the interaction term. This suggests another possible reason why High-Quality outperforms the other Quality levels of Center-based care; it reduces the rate of disruption more, and the reduction lasts longer. Among Home-based Care, we are seeing the same pattern. The main effects of quality have all increased. All main affects seem to drop out as time passes. There is also now a main effect of Unknown quality, both in Center-based care, HR = 0.68, $\beta = -0.38$ $p < 0.001$, and Home-based Care, HR = 0.66, $\beta = -0.41$ $p < 0.001$. The *Age at Entry* retains the same protective effect as *Age* in prior models, HR = 1.15 $\beta = 0.14$ $p < 0.001$.

Model 7 includes our demographic variables of interest, to mostly the same effect as Model 5. *Age at entry* shows a very similar effect to *Age at entry* in model 6, and *Age* in Model 5, HR = 1.15 $\beta = 0.14$ $p < 0.001$. So, we are seeing a consistent increase in rate of disruption with age. The *Male* variable also shows a significant increase in Hazard of disruption, HR = 1.09, $\beta = 0.09$ $p < 0.001$. Race and Ethnicity variables still show no significant change in rate of disruption. The main effects of Center-based and Home-based care remain unchanged across levels of quality. Among the Center-based Care, we still see that the main effects overtaken by the interaction terms after about 1 year of time spent in foster placement. The one possible exception is Center-based High-Quality, which still shows a greater reduction in Hazard than

Center-based Medium-Quality, but erodes at the same rate, indicating that the effect lasts longer; this, again, indicates that High-Quality outperforms Medium-Quality in terms of longevity, at least for Center-based care. Among Home-based care, the protective main effects are largely unchanged, with the interaction terms still tending to erode the main effects after about a year or more, possibly lasting longer than Center-based counterparts. It is worth noting that Home-based Low-Quality retains a significant protective effect in Model 7, HR = 0.51, $\beta = -0.68$ $p < 0.001$. In Model 5, this reduction of hazard lost its significance when demographic variables were added, but now that the model includes an interaction with time, that main effect stays significant.

## Discussion

The relationship between ECE and disruption is far from simple. Before returning to our original hypothesis, a few specific findings must be made clear. First, it seems that at every level of quality and type, the use of subsidized child care is associated with a significant decrease in the rate of disruption. The only apparent exception is Home-based High-Quality care, which may be an artefact of a small sample size. Second, in all cases (again, except for the rare Home-based High-Quality category) all protective effects were highly-time dependent. This introduces a new dimension in which to compare outcomes; we can compare based on the decrease in hazard, and how long that decrease in hazard lasts. With these dimensions in mind, we can return to our original hypotheses.

Home-based Care does seem to outperform Center-based care on the rate of disruption occurrence. It must be said, however, that that may have been due to the relationship between type, quality, and sample size. Medium-Quality is the most common certification level in both Type categories, and in at this quality level, Home-based Care does seem to outperform center-based care. And it was likely on the basis of this advantage that Home-based care seemed to show a more significant reduction in hazard than Center-based, when averaged across quality levels and when looking at the early stages of placement. For the other two levels of quality, Home-based and Center-based ultimately seem to have the same reduction of hazard. On the basis of longevity of effect, however, it seems that the protective effects of Home-based Care may outlast that of Center-based care, at least at the quality levels that occur enough to accurately estimate.

Moving on, it seems that increasing Quality certification level does not uniformly decrease the rate of disruption. For Center-based Care, High-Quality does seem to outperform Medium Quality care in terms of rate of disruption early on in the child's placement. Low-Quality certification of care seems to have the same effect on hazard as Medium for home-based care; in Center-based care, it has the lowest estimated regression coefficient, but also the widest confidence interval, so we cannot confidently say it differs from Medium- or High-Quality care in terms of hazard. In terms of longevity, a High-Quality certification may mean a longer-lasting effect; High-Quality seems the longest-lasting among Center-based, with Medium- possibly being the longest-lasting in the Home-based resources. But again, the small sample of Home-based High-Quality care makes that a less certain statement. What is clear is that there is not a linear relationship between Quality and rate of disruption.

Also, in every model we see high variability in the individual frailties associated with client identity. The standard deviation of most of the models is estimated to be sd = 0.96. This is a measure of the degree to which the separate frailties of each individual deviate from the baseline hazard, and in this case can be interpreted like a hazard ratio, HR=2.62. This means many individuals will show up to 261% increased over those of average frailty, for reasons unrelated to the ECE type or quality variables. Even in our most specified model, the frailties showed a high degree of variability, sd = 0.79, HR = 2.20. So there still remains a large amount of unexplained heterogeneity among the sample. Future studies will need to do more to identify relevant predictors of disruption.

And there are many likely candidates. For one, there is the issue of geography. It is not reasonable to treat all foster families as if they have access to all Child Care resources. Those in more rural settings will likely have to few or even no options to choose from. In more urban settings, there will likely be more options for the parents, but that introduces the selection bias of the parents. More conscientious parents may seek out ECE providers of higher quality, but that conscientiousness too may be a significant predictor of stability, with or without ECE. Indeed, we have not included any measure at all of the "climate" of the foster home itself. These and more are likely powerful predictors of stability that must be accounted for to get a more accurate picture of the influence of ECE.

Moreover, this study does not elucidate the exact mechanism of *how* having access to ECE might affect foster care stability. Prior research does suggest that higher-quality ECE programs have greater benefits to the child's behavioral and social development. This in turn could improve the relationship between the foster parent and foster child and thereby improve the stability of the foster placement. However, given the diversity of reasons foster children are removed from foster families, it is difficult to say for sure based on the current study alone. One might also assume that ECE access improves the financial stability of foster families by removing or lessening the expense of child care. As our data set does not include information on the socioeconomic status of the families, this variable could not be counted for. Moreover, we do not know how many families in the control group enrolled in ECE and paid for it out of pocket. Without this information, there is little way to parse out the influence of socioeconomic status. It does seem probable that the influence of subsidized ECE is helpful for reasons other than the fact that the parent gets a break from having to personally care for the child while the child is in daycare. If this small respite were the only contributing factor, then the type and quality variables would not have the wildly differing effects on Hazard. But without an alternate condition where the child stays home and the parents go to daycare, it is difficult to directly test whether it is simply the temporary separation of foster parents from the responsibility of direct child care that increases stability. Still, through one mechanism or another, Subsidized ECE does seem to improve foster stability, and the extent of that improvement does seem related to ECE type and Quality. More research is needed, however, to explore how and why ECE type and Quality influence foster placement stability.

Ultimately, the worthiness of early child care education must be measured in educational outcomes. Other literature shows the many benefits foster children receive from ECE. It is on the basis of these reasons that subsidized ECE is a part of Service as Usual for foster families nationwide, and should remain so. However, the outcome of interest here is the longevity of foster placements. And it will take more than Service as Usual to improve the lives of foster children and families. It is clear that Subsidized ECE for foster families is not equally beneficial for all families in all ECE providers at all times. Further research into the nuance of how ECE characteristics affect stability is both necessary and worthwhile.

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## Appendix A

*Summary of Star Category Criteria**

| 1 Star Plus | 2 Stars | 3 Stars |
|---|---|---|
| Director evaluates personnel annually, using Oklahoma Core Competencies guidelines. | Accredited by national accrediting body approved by Child Care Services OR compliant with Head Start Performance Standards. | Accredited by national accrediting body approved by Child Care Services OR compliant with Head Start Performance Standards. |
| Provides detailed Employee Handbook | OR | AND |
| Registered with OK Professional Development Registry (OPDR) | Meet all 1+ Star criteria, plus the following: | Meet all 1+ and 2 Star criteria |
| Personnel OPDR certified | Full-time, on-site employment of Master Teachers, certified in Oklahoma Early Learning Guidelines | |
| Policy/Procedure manual on site. | One Master Teacher for 30 children. | |
| Two personnel meetings per year | Master Teachers work directly with children and other teaching personnel. | |
| Director must have 2 college credits or 30 clock-hours in 12 months prior to Star certification, and per year. | Separate spaces for variety of activities, including music, movement, math, and science or nature. Two must be outdoors. | |
| Personnel must have 2 college credits or 20 clock-hours of professional development per year. | Uses Oklahoma's Early Learning Guidelines to plan lessons, curriculum. | |
| One personnel per 30 children must work towards Master Teacher Qualifications | Two parent conferences per year, including written reports. | |
| Personnel in training must be trained in Oklahoma's Early Learning Guidelines | Program assessed every year by Child Care Services. | |
| Separate spaces for variety of activities, including music and movement. | Goals and policy updated every year from surveys, Child Care Services. | |
| No TV for children under 2 years. | Written plan for professional development. | |
| System for communicating with families | Personnel participate in program evaluation, goals. | |
| Families welcome in facility at all times. | | |
| Annual conferences with parents | | |
| Two family meetings or special events per year. | | |
| Families informed of program through multiple media. | | |
| Families participate in policy development | | |

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| Personnel/Parents surveyed annually. | | |
| Yearly Inventory. | | |
| ***All ECE programs licensed to operate, or those granted a 6-month permit, are automatically given a 1 Star rating. Note that '1 Star' and '1 Star Plus' are separate categories.** | | |