# GEOGRAPHIC PLACEMENT STABILITY OF CHILDREN IN FOSTER CARE

by

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## DEDICATION

This dissertation is dedicated to my parents, Melvin and Lorraine Kulbicki. Thank you for everything.

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## LIST OF ABBREVIATIONS

Administration of Children and Families……………..…………………………..…...ACF
Adoption and Foster Care Analysis and Reporting System……………………..….AFCARS
American Community Survey………………………………………………………ACS
Children's Bureau………………...……………………………………………….CB
Child Protective Services.......................................................................................CPS
Connecticut………………………………………………………………………...CT
Department of Children and Families ..................................................................... DCF
Health and Human Services…………………………………....…………………....HHS
Hierarchal Linear Modeling……..…………………………………………………HLM
Hierarchal modeling ............................................................................................... HM
Institutional Review Board .................................................................................... IRB
Federal Discharge Reason…………..………………………………………………FDR
Geographic information systems…………………………………………………GIS
Least Absolute Shrinkage and Selection Operator............................................... LASSO
Multinomial Logistic Regression ........................................................................... MLR
National Child Abuse and Neglect Data System ...............................................NCANDS
National Youth in Transition Database ....................................................................NYTD
Ordinary Least Square ............................................................................................ OLS
Principal Component Analysis................................................................................ PCA
Research Question .................................................................................................. RQ
United States ...........................................................................................................US

## ABSTRACT


GEOGRAPHIC PLACEMENT STABILITY OF CHILDREN IN FOSTER CARE

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Children placed in the foster care system are some of the most vulnerable children due to the abuse and neglect that they experienced that led them to foster care. Once these children enter foster care, they continue to face challenges by having multiple foster care placements, resulting in geographic instability in neighborhoods and disruptive environmental changes for children in foster care. The geographic placement instability of children in foster care is multifaceted with effects on (1) children's foster care outcomes to achieve permanency, (2) successful transition to adulthood after foster care, (3) neighborhood changes, and (4) types of foster care placements. There are several reasons why a child may have multiple foster care placements, including the child's behavioral needs or the placement setting's availability which can drive the decision-making process on where to place children. Children who have multiple placement settings face an inordinate amount of instability by not knowing when and if they will have to change placements. Researchers and practitioners do not understand the effects of distance between the child's home and all foster care placements and the distance between foster care placements. This dissertation analyzes the geographic impact of children in foster care using 15 years of foster care placement data from Connecticut's Department of Children and Families.

This dissertation uses a variety of statistical and geographic models, including hierarchal models, multinomial regression models, hot spot analyses, and negative binomial models, to determine how distance affects placement stability. Foster care involves geographic challenges related to multiple foster care placements, resulting in multiple shifts in neighborhood environments which can impact the child developmentally and academically. This research found that the location of the foster care placement had a greater impact on a child's foster care outcomes than the location of the child's home before they entered foster care.

# 1. INTRODUCTION

*"Children are the world's most valuable resource and its best hope for the future." - John F Kennedy.*

Maintaining the well-being, health, and safety of all children is critical to modern society's success. Children involved in child welfare are one of the most vulnerable populations due to the trauma, abuse, and neglect they experienced before entering the child welfare system (Perry, 2006; Takayama et al., 1998). When a child is suspected of suffering abuse or neglect, child protective services (CPS) assess the child's situation. If a child can no longer safely remain in their home, they are placed in foster care. Foster care involves geographic challenges related to multiple foster care placements, resulting in multiple shifts in neighborhood environments which can impact the child developmentally and academically.

On September 30, 2020, 407,493 children were in the foster care system (U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2021). Typically, children enter foster care because they have gone through a trauma that could include abuse (mental, physical, or sexual), neglect, or the inability of a parent to no longer care for the child as a result of incarceration, abandonment, or death (Franzén & Vinnerljung, 2006; Leve & Chamberlain, 2007; Perry, 2006). Nationally, 43 percent of the children in foster care were in foster care for less than a year, and 49 percent of the children were reunited with their parents or their primary caretakers (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2020).

Figure 1-1 shows the number of children in the U.S. foster care system from 2000 to 2019 (The Annie E. Casey Foundation, 2021). The average number of children in the U.S. foster care system from 2000 to 2019 was 450,159. In 2000 the U.S. had the most children in foster care, with 544,614 children, followed by 2001 with 544,303 children, a less than 0.1% decrease between the two years. Since 2000 the number of children in foster care has steadily declined. The fewest number of children in the U.S. foster care system was in 2012 with 397,091 children, and in 2011 with 397,885 children, a 37 percent decrease from the peak in 2000. Since 2012 there has been a slight increase in the number of children in foster care. However, the numbers have not reached the record-high number of children in 2000.

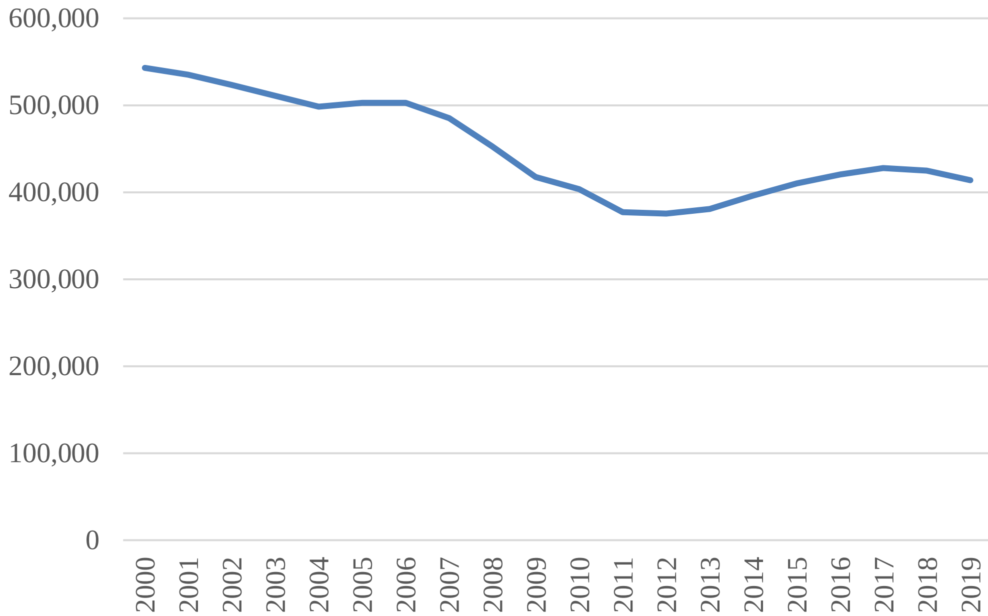


**Figure 1-1. U.S. Foster Care Entries from 2000 to 2019**
(The Annie E. Casey Foundation, 2021)

Foster care placements can include foster homes (relative or non-relative), group homes, institutions, supervised independent living, or trial home visits. An essential focus of scholars has been the notion of "successful" foster care placements (James et al., 2004). There are multiple reasons why a child may not have a "successful" foster care placement, which could include: the child's behavior, a mismatch or unrealistic expectations of the foster family and child, or a divorce or the birth of a biological child of the foster family or other unexpected life events (James et al., 2004). The arrangement of a new foster care placement occurs when a child does not have a "successful" foster care placement. Multiple "unsuccessful" foster care placements can cause delays in permanency outcomes, including reunification with parents, adoption, and guardianship

(Connell et al., 2006). The longer a child spends in foster care, the higher their risk of experiencing multiple placements (Koh et al., 2014) due to “unsuccessful” foster care placements.

This dissertation examines the significance of geography on foster children’s outcomes in Connecticut (CT) from 2000 to 2015. The number of children in the Connecticut foster care system represents one percent of the children in the U.S. foster care system (The Annie E. Casey Foundation, 2021). Figure 1-2 shows the number of children in foster care in Connecticut. The fewest number of foster children in Connecticut was in 2015 with 3,908 children, followed by 2014 with 4,079 children. Connecticut saw the sharpest decrease in foster care children from 2006 with 7,448 children to 2007 with 5,591 children, nearly a 35 percent decrease. The average number of children in Connecticut’s foster care system from 2000 to 2019 was 5,413. Overall, the rate of children in Connecticut’s foster care follows the national patterns in the U.S., with a steady decline in the number of children in foster care.

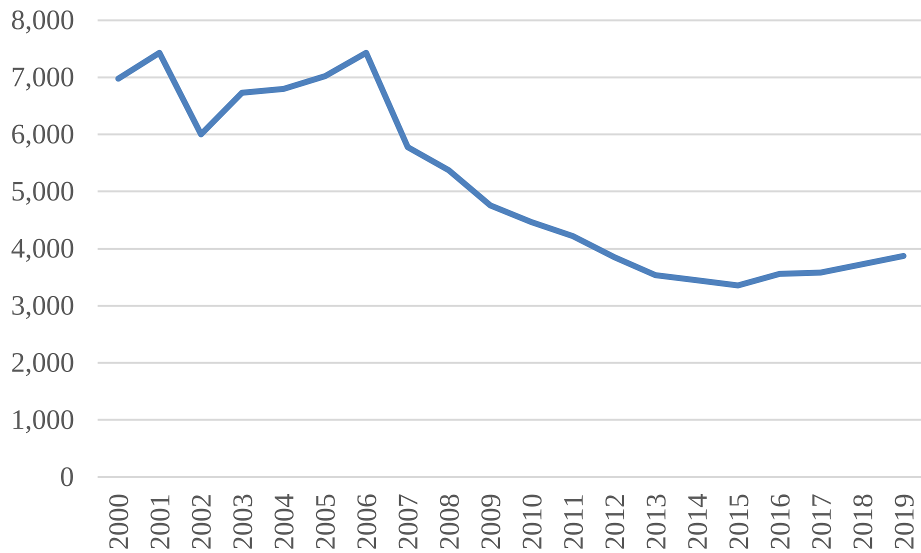


**Figure 1-2. Connecticut Foster Care Entries from 2000 to 2019**
(The Annie E. Casey Foundation, 2021)

Distance is an essential measure in understanding a child's foster care outcomes and placement stability and is considered in every research question of this dissertation. A variety of statistical and geographic models, including hierarchal models, logistic regression models, multinomial regression models, hot spot analyses, ordinary least square (OLS) regression, and negative binomial models, are used to determine the outcomes of placement stability through understanding the effects of (1) children's foster care outcomes to achieve permanency, (2) successful transition to adulthood, (3) neighborhood changes, and (4) types of foster care placements. These geographic analyses provide a root of understanding of how geography and change in geography can impact children's outcomes in foster care.

# 2. LITERATURE REVIEW

Foster care is meant to be a short-term solution for children who can no longer safely remain in their homes. Children who are placed in foster care have often experienced physical, sexual, or emotional abuse, neglect, abandonment, or a parent no longer being able to care for a child due to incarceration, death, or a parent's voluntary surrender of a child (Chernoff et al., 1994; Freisthler, 2006; Lery, 2009). In these situations, child welfare agencies assume the responsibility of a child when they can no longer safely stay in their home (Zuravin & DePanfilis, 1997). Child welfare agencies strive to protect the safety of children by creating a stable environment. One aspect of a stable environment is to ensure that children have placement stability while in the foster care system. The federal definition of placement stability of a child is having less than two foster care placements per foster care episode (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2019a). Despite these efforts, many children in foster care experience multiple foster care placement settings, resulting in placement instability (Koh et al., 2014).

## 2.1 Foster Placements

The federal definition of foster care placements used for federally reporting to the Adoption and Foster Care Analysis and Reporting System (AFCARS) is that "Placement occurs after removal and is the physical setting in which a child finds himself or herself, that is, the resultant foster care setting. A new placement setting results when the foster care setting changes, for example, when a child moves from one foster family home to another or to a group home or institution" (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2020). State child welfare agencies use this definition to report foster care data to the federal government semi-annually as part of the requirements of AFCARS. This standard definition of foster care placements allows consistent reporting across states and jurisdictions.

Permanency planning is crucial to helping foster care children (Salazar et al., 2011). Finding permanent housing solutions is a goal for children exiting foster care. Permanent housing placements include homes through adoption, guardianship, or reunification with family members (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2020). However, finding a permanent housing solution is sometimes not achievable for all children. When children do not achieve permanency they could exit foster care through emancipation or be transferred to another agency, such as juvenile justice (Gypen et al., 2017).

The Adoption and Safe Families Act of 1997 is legislation that requires that the state hold a permanency hearing within 12 months of a child entering foster care; this is six months sooner than previous legislation (Biklen, 1999; Furbish, 1998). This legislation ensures that placement decisions are made quickly by caseworkers and juvenile court judges, who are often the key decision-makers for assigning foster care placements and establishing permanency. Generally, caseworkers and juvenile court judges are guided by state policies or practices to determine where a child is placed in foster care (Zuravin & DePanfilis, 1997). However, the decision on a child's placement is limited to the availability of foster homes (McBeath & Meezan, 2007).

State laws may vary and give preference to particular foster care placements and have different determinations on a child's "best interests" (Child Welfare Information Gateway, 2018b). For instance, best interest factors are only statutes in 22 states and Washington D.C. (Child Welfare Information Gateway, 2020a). Best interests for children in foster care vary within these states that prioritize the emotional relationship children have with family members (parents, siblings, or kin) or account for the children's mental and physical health (Child Welfare Information Gateway, 2020a). As it will be the case study for this dissertation, Connecticut merits special mention. Appendix A shows specific child welfare laws in Connecticut, including reasonable efforts to achieve permanency and reunification, placement with relatives, foster care eligibility after 18, and the child's best interest.

Connecticut's Department of Children and Families (DCF) takes many considerations to ensure the safety of children. Connecticut DCF considers "the children's return to their birth families, including extended family, when available as the first consideration of a foster care placement" (Connecticut Department of Children and Families, 2021). When a child in Connecticut's foster care system needs foster care, a social worker known as a "matcher" works to find an appropriate home. Connecticut DCF's policy and good practices governing placements into foster homes include:

considering the geographic proximity to the child's own home or school; keeping siblings in the same foster home (when feasible); and limiting the number of children who may reside in a foster home (Connecticut Department of Children and Families, 2021a).

Placement "success" is multifaceted, considering the child's needs and the conditions and availability of the foster care placement. However, the driving mechanisms of a successful foster care placement remain complicated and are driven by the child's needs. A child may need to change foster care placements for a facility with specialized health care due to the child's behavior, a mismatch between the foster family and child, unrealistic expectations of the foster family, or an unexpected life event of the foster family, such as divorce or the birth of a biological child (James, 2004). Whatever the reason the placement did not work out for the child, the foster care agency must find a new placement.

The geographic location of the foster care placement can impact the success of a child's placement and the child's outcome. Becker et al., 2007, found that urban districts in Florida had a worse probability of successful foster care exits related to geography. However, this contradicts a Tennessee study that found that children in urban areas had better foster care outcomes (Glisson et al., 2000). The state's policies and practices could influence these contradictory findings of urban and rural placement settings and the overall geographic layout of the state, with some states having more significant urban influences than other states.

Some children remain in the foster care system until they age out of the system. The age at which a child ages out of foster care is typically 18 or 21 and varies by state.

Connecticut allows children to stay in foster care until they are 21 through an extended foster care program (Juvenile Law Center, 2020). The foster care placements of these children merit special attention since the outcomes of these children are tracked through the National Youth in Transition Database (NYTD). The Administration of Children and Families (ACF) began collecting outcome data for the NYTD through Public Law 106-169, the *John H. Chafee Foster Care Independence Program* to understand the challenges of youth aging out of foster care. This law enables the federal government to assess the state's performance in providing independent living programs and measure outcomes for youth through a survey administered on the youth's $17^{th}$, $19^{th}$, and $21^{st}$ birthdays.

The outcomes that the NYTD survey collects are financial self-sufficiency, experience with homelessness, educational attainment, positive connections with adults, high-risk behavior, and access to health insurance for children who have aged out of foster care (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2012). The NYTD data provides states with an opportunity to understand what services children in foster care receive at 17 years old. This data, partnered with the AFCARS data, can provide a picture of foster care placements and outcomes for youth in foster care. Especially since many former foster care youth experience difficulties transitioning into adulthood and face numerous challenges (Berzin et al., 2011).

## 2.2 Multiple Foster Care Placements

The longer a child spends in foster care, the greater the likelihood of experiencing multiple placements (Koh et al., 2014). Multiple foster care placements are often linked to poor health outcomes and negative behavioral outcomes, such as trouble with the law, higher pregnancy rates, violence in dating relationships, increased likelihood of adolescent parenthood, behavioral problems, criminal conviction, and school dropouts (Batsche & Reader, 2012; Connell et al., 2006; Leathers, 2006; Newton et al., 2000; Rubin et al., 2007; Shpiegel & Cascardi, 2015; Simms et al., 2000). Children in long-term stable placements show significant improvements in their health status, physical growth, and education (Simms et al., 2000) and are less likely to attend new schools or move to new neighborhoods (Batsche & Reader, 2012; Weiner et al., 2011). Finally, children in foster care with two or more placements are significantly less likely to be reunited with their family members (Connell et al., 2006).

The federal data reported in 2017 show that 35 percent of those who spent more than a year but less than two years in foster care had more than two foster care placements, which is a 20 percent increase from children who spent less than a year in foster care (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2019b). Fifteen percent of the children who spent less than a year in foster care had two or more foster care placements (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2019b).

Foster care placements can be geographically disruptive, with children often facing numerous school changes (Pecora, 2012; Pecora et al., 2006), resulting in educational failure and risky health behaviors such as delinquency, drug use, and teen pregnancy (Leve & Chamberlain, 2007). Children in the child welfare system are not limited to educational failures since the child welfare system is systematically linked to the juvenile justice system. Children connected to the child welfare system and the juvenile justice system have an increased risk of low academic performance and school failure (Leve & Chamberlain, 2007). These multiple placements also disrupt the social network that is part of a child's school and neighborhood support network. Nancy Hughes, president and CEO of Volunteers of America [Illinois], reported a foster care youth saying, 'Tell me I'm going to the same school and I can handle everything else' (Foltz, 2011).

Many children in foster care are academically behind children their age and have poor academic performance that is associated with placement instability (Koh et al., 2014) and multiple school changes that can influence and reduce their success in school and after graduating from school (Pecora, 2012). There are serious consequences of academic failure, including behavioral and health outcomes such as delinquency, drug use, and teen pregnancy (Leve & Chamberlain, 2007). It is estimated that children with multiple educational settings typically take four to six months to recover academically after each foster care placement change (Casey Family Programs, 2009).

Multiple placement settings also affect a child's ability to form trusting relationships (Newton et al., 2000). A child with a social network of adults that they can trust and friends that they can rely on means everything to a child (Perry, 2006). The cohort-1 NYTD results reported that 92 percent of youth in care and 89 percent of youth not in care do have a positive connection with an adult (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2016).

## **2.3 Foster Care Placement Types**

There are eight categories of foster care placement settings denoted in the AFCARS federal guidelines: pre-adoptive home, foster family home (relative), foster family home (non-relative), group home, institution, supervised independent living, runaway, and trial home visit (U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2018). The distribution of foster care placement setting types has remained relatively consistent since 2000. Figure 2-1 shows that most foster care placements are in foster families' homes with a relative or non-relative. Nationally, 46 percent of the placement setting types are foster family non-relatives, and 31 percent of foster family placement types are foster family relatives (*Children in Foster Care by Placement Type | KIDS COUNT Data Center*, 2021).

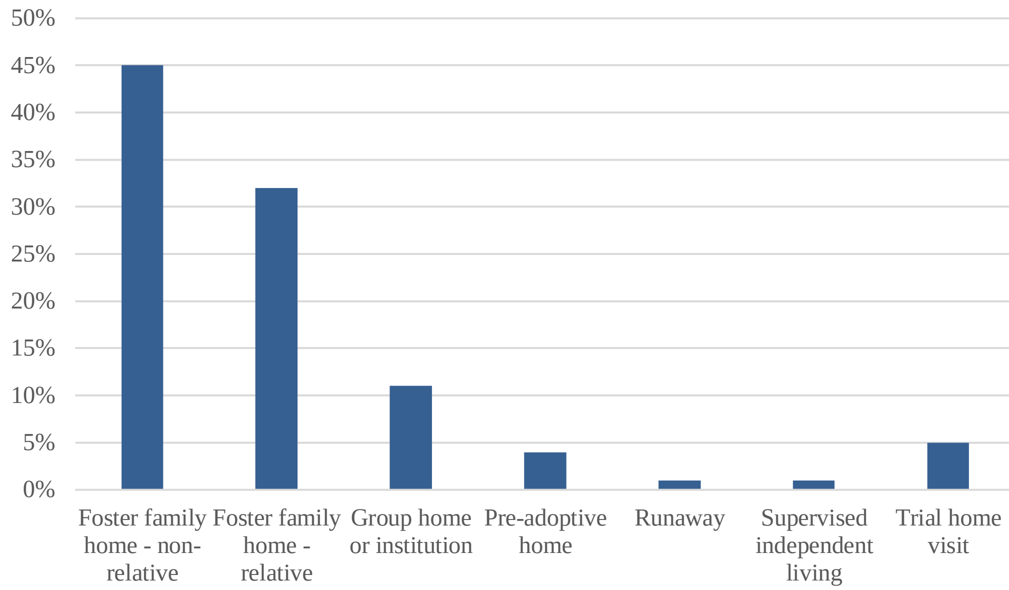


**Figure 2-1. 2019 U.S. Foster Care Placement Setting Types**

A relative foster family home placement can also include kinship foster care placement. A kin foster care placement is where ‘there is a psychological, cultural or emotional relationship between the child or the child’s family and the foster parent(s) and there is not a legal, biological, or marital connection between the child and foster parent” (U.S. Department of Health and Human Services, Administration for Children and Families, Administration Children, Youth and Families, Children’s Bureau, 2020). States rely heavily on kinship care for foster care placements (Messing, 2006). Studies have found mixed well-being indicators for kinship placements, with kinship placements having no effect on children’s health (Font, 2014), which contradicts earlier research, suggesting that kinship placements may lead to better outcomes for children by creating a stable and safe environment (Messing, 2006).

Foster care placements in homes of a relative or a non-relative have more favorable outcomes for children than when children are placed in institutions or group homes. Ryan et al., 2008, found that when children are placed in group homes, they are two and a half times at greater risk of delinquency. Additionally, when children are placed in group homes or institutions, they are less likely to develop individual characteristics (Marinkovic & Backovic, 2007). Children’s lack of personal characteristics in group homes can be linked to the lack of a sense of belonging or uniqueness (Marinkovic & Backovic, 2007).

## 2.4 Foster Care Characteristics

Age and race are two foster care characteristics frequently analyzed since they often predict a child’s foster care outcomes and are strong indicators for reunification with a child’s family (Connell et al., 2006). A longitudinal study found that age is associated with multiple placements; however, the same study found that race and sex were not significant in multiple placements, resulting in placement changes (Connell et al., 2006). Additionally, in other studies, gender has not been a significant factor in foster care outcomes (Becker et al., 2007; Connell et al., 2006; Courtney, 1994). The number of males and females in the foster care system has remained balanced from 2006 to 2016, with males representing 52 percent of the foster care population (Child Welfare Information Gateway, 2018b).

Younger children, especially under one, tend to enter foster care more frequently than older children and are much more likely to be adopted (Wulczyn et al., 2002). The median age of a child entering foster care in 2018 was 7.6 years old, and the age of foster care children has been consistently getting younger since 2006 (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2020). Wulczyn et al., 2002, research supports the nationally reported data that children 12 years old and older are less likely to find a permanent home (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2016).

How a child exits foster care is also related to the age they enter foster care. Becker et al., 2007 found that younger children were more likely to reunify with family members than older children. Younger children in foster care are also more likely to have fewer behavioral problems than older children (Berrick et al., 1993; Redding et al., 2000). Further, older children experience more placement instability than younger children, which is often associated with the length of time spent in foster care (Berrick et al., 1993; Koh et al., 2014; Redding et al., 2000). Older children often end up in group home foster care placements because of their troubled background or behavioral problems and the lack of families that can take on their emotional needs and are less likely to be adopted (Becker et al., 2007; Snowden et al., 2008; Wells & Guo, 1999).

Children who are non-White are disproportionally over-represented in foster care (Shaw et al., 2008). AFCARS data reported in 2018 that 44 percent of the children in foster care were White, 23 percent were Black/African American, and 21 percent were Hispanic or Latino (of any race) (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2020). The number of children entering foster care by race over the past ten years is changing. The AFCARS data reported that the number of Black/African American foster children has decreased from 2008 to 2018, while White and Latino children have increased in the foster care population (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2020).

Race and ethnicity are significant factors in a child's foster care outcome, with non-White children having poorer outcomes (Becker et al., 2007; U.S. Department of Health & Human Services, Administration on Children, Youth and Families, 2019). Notably, Black/African American children are less likely to achieve permanency than White children (Kemp & Bodonyi, 2000) and are more likely to be in foster care longer and have more foster care placements (Courtney & Wong, 1996; Watt & Kim, 2019). Additionally, while in foster care, non-White children are less likely to receive support services and treatments than White children (Ayón, 2009; Fluke et al., 2003).

## 2.5 Geographic Influences and Predictors

The connection of geography and social work as an element of public health has long been considered by scholars. Investigation into these linkages traces back to the late nineteenth century when social worker Jan Addams of Hull House used surveys and maps in Chicago neighborhoods to understand social conditions (Felke, 2006; Rine et al., 2012; Tompkins & Southward, 1999). Addams's work, known as the Hull House Maps, was the first spatial analysis to understand child labor economic injustices and integrate spatial thinking into social work (Tompkins & Southward, 1999). The practice of maps in social work has evolved from the paper maps of the late nineteenth century to today with the use of Geographic Information Systems (GIS).

Geography can play an essential role in creating a stable environment for children through the science of GIS. GIS is particularly useful for improving decision-making and understanding accessibility to services for children in child welfare (Felke, 2006; Felke, 2015; Hillier, 2007; Rine et al., 2012). Decision-making in child welfare is rooted in three areas (1) prevention, (2) investigation, and (3) program planning. These areas are rooted in understanding "where" events are occurring. Common child welfare questions include: where are the children, where are the services, and where are the foster families (Kulbicki, 2014). These common social work questions are rooted in Tobler's first rule of geography, which states, "all things are related, but nearby things are more related than distant things" (Goodchild, 1998).

Maintaining a sense of normalcy is vital for children in foster care. The proximity to a child's home is critical for creating a sense of normalcy. Placing a child in foster care in closer proximity to their home creates a sense of normalcy and increases unification with the birth parents (Rine et al., 2012), and creates better outcomes related to academic performance and maintaining a connection to the parents (Huang et al., 2016). Illinois has used a geographic-based tool called SchoolMinder to help understand a child's proximity to school by searching for foster care placements within the same school district. The SchoolMinder program reduced the average placement distance from

9.9 miles to 2.5 miles in Cook County (Chicago) and for the remaining counties in Illinois from 22.5 miles to 11.4 miles. These placement changes increased a child's school stability by 50 percent (American Bar Association Center on Children and the Law, Education Law Center and Juvenile Law Center, 2011).

Prevention programs in child welfare focus primarily on child abuse and neglect, which is often a predictor of children entering foster care. Geography-based prevention research in child welfare focuses on spatial patterns of child maltreatment and neighborhood indicators (Freisthler et al., 2007; Lery, 2009). In particular, GIS is utilized in child maltreatment research to understand hotspots and neighborhood characteristics (Coulton et al., 2007). There is a strong correlation between socio-economic characteristics associated with neighborhoods and the number of cases reported to CPS (Coulton et al., 2007). Several methods have been used to understand spatial patterns using exploratory spatial data analysis (ESDA), hot spot analysis, spatial regression, and spatial autocorrelation to locate neighborhoods with a high incidence of reports to child protective services.

Spatial autocorrelation has been used in many studies that have looked at child maltreatment and neglect in relation to poverty and other community characteristics. In particular, the Moran's *I* statistic has been used to identify regions with adverse effects (Askar & Zuefle, 2021). The literature has found that poverty and child maltreatment are geographically linked (Klein, 2011; Paulsen, 2004; Voss et al., 2006). A national hot spot analysis shows that child poverty is clustered and associated in counties with higher poverty rates (Voss et al., 2006). Similar to the national findings, a state analysis in

Virginia used ESDA and spatial autocorrelation to identify community risk indicators, such as poverty and a child's wellbeing, and found comparable trends to the national portrait with high poverty areas linked to child maltreatment (Anselin et al., 2007). The use of GIS helps community's develop policies (Anselin et al., 2007; Frankenfeld & Leslie, 2019; Yang et al., 2016) and understand neighborhood perceptions (Coulton et al., 2007; Leslie et al., 2022) which could assist children and families.

Multiple studies support that poverty and household stress are key socio-economic indicators related to children reported to CPS (Coulton et al., 2007; Courtney et al., 2004; Freisthler, 2006; Freisthler, Bruce, et al., 2007). Freisthler, Gruenewald, et al., 2007, conducted a study across three California counties with diverse racial backgrounds and found that poverty was more significant than race in child maltreatment reports. The research also noted that substantiated maltreatment reports were more likely with Black/African American children than with White or Hispanic children.

The national and the county level state analysis follows similar trends of smaller geographic units associated with neighborhood levels of poverty and child maltreatment (Berzin et al., 2011; Cardazone et al., 2014; Coulton et al., 2007; Earnst, 2000; Freisthler, 2006, 2011; Thurston et al., 2017). Census tracts and zip codes are the primary geographic units of measurement that ecological studies have used to understand local neighborhood influence on child maltreatment (Dorch et al., 2010; Freisthler, 2011; Hillier, 2007; Klein, 2011; Lery, 2009). Census tracts are commonly used to define neighborhoods in public health, criminal justice, and social work research. However, Census tracts may not align with residents' perception of neighborhood boundaries since they are designed for Census data collection and not thought of as neighborhoods by their residents (Coulton et al., 2001). Even though Census tracts may not align with neighborhood perceptions, they are commonly used because of the robustness of Census information (i.e., the American Community Survey (ACS) and the decennial Census) which provides detailed population and socioeconomic information (U.S. Department of Commerce, Census Bureau, 2017).

Vinson et al., 1999 found that maltreatment areas are geographically clustered around neighborhood cohesion variables. Other spatially correlated indicators include lower maltreatment cases near child care resources (Mobley et al., 2006). Freisthler et al., 2007, found that neighborhoods with higher spatial concentrations of stores that sell alcohol also had higher reports of maltreatment, which suggests that community actions limiting the density of these stores could assist in child welfare intervention strategies. An additional maltreatment neighborhood indicator is housing stress, which is often indicated by renters who pay more than 35 percent of their rental income, which is a consistent stress for families associated with child maltreatment (Earnst, 2000).

Intervention policies and practices are designed to assist a child and their family when they have been identified as being maltreated (Wiggins et al., 2007) and focus on the early stages of family and child problems, including access to services (Batsche & Reader, 2012; Freisthler, 2011). Fisher et al. 2009 developed a framework based on evidence-based interventions, including identifying foster children’s needs for services, providing resources, implementing interventions, and therapeutic programming. The use of geography has been instrumental in child welfare intervention in identifying services

(Hardt, 2013). Typical services needed by a foster family may include therapeutic intervention and support, homemaker services, psychological evaluations, attending to the child's personal needs of clothing and special equipment if needed, programs transitioning teens to self-sufficiency, alcohol and substance abuse diagnosis, pregnant and parenting teen services (Child Welfare Information Gateway, 2018a). Similar to the prevention research that has been done, GIS is used to help find the locations of facilities for interventions (Hardt, 2013). However, once the child is in the foster care system, they need to be with a family who understands the need for and the importance of access to medical service and has a lifeline to the department of family services offices and employees, which integrates intervention and support.

The availability of services has an overwhelming impact on a child's physical and mental well-being (Goldhaber-Fiebert et al., 2012). Social workers have started using GIS to understand service accessibility in one-dimensional applications that look at a map when accessibility issues are often more geographically complicated. These applications typically use buffer analysis to understand accessibility (Rine et al., 2012). With the spatial depiction of resources on a map, the inequality of health services can be better accounted for and allocated across social service programs (Wong & Hillier, 2001). Accessibility to child welfare services and child welfare offices has been the most studied geographic intervention approach thus far in the literature (Batsche & Reader, 2012; Freisthler, 2011; Rubin et al., 2007; Weiner et al., 2011).

When a child welfare agency can anticipate the needs of children and families, the agencies can plan for resource allocation and increase public awareness of programs.

Program planning has many geographic components, such as locating new foster care offices and the distribution of the child welfare workforce (Mandayam & Joosten, 2016). Mapping child welfare assets can assist child welfare offices by focusing on where resources are located or identifying resource gaps or deserts (Hillier, 2007). Studies like Batsche & Reader, 2012, can help social workers use GIS for program planning by anticipating housing needs for youth aging out of foster care. Batsche & Reader, 2012, examined the housing needs for older youth in Hillsborough County, Florida, and used GIS to find safe, affordable housing for youth with various needs, including safe and affordable housing with access to education and public transportation. By implementing the use of geostatistical methods, agencies will be able to better understand their communities (Sikder & Züfle, 2019, 2020).

## **2.7 Research Opportunity**

As children experience multiple foster care placements, the ability for consistent services and family connections can be challenging with increased distance and less familiarity with neighborhoods and families. Combining social work and public health geography elements can enhance the understanding of foster care placements and a child's experience in foster care (American Public Health Association, 2018; Dummer, 2008). By increasing geographic methods and practice in social work, practitioners and scholars can understand geographic differences across states and urban areas.

There is a substantial opportunity to gain our understanding of the geographic challenges associated with children with multiple placements in foster care by linking both the fields of geography and public health to benefit scholars and practitioners. Child welfare can use geography to understand the geographic elements of neighborhood changes that a child experiences with multiple foster care placements. By understanding the impact of neighborhood change and the distance between foster care placements, the field of social work can better provide services to children before they enter foster care and while they are in foster care.

# 3. METHODS

This dissertation examines the geographic changes children experience when placed in foster care. There are two main components in understanding a child's geographic challenges in foster care. The first component is understanding the geographic differences a child experiences in foster care by examining the children’s outcomes and placement type. The second geographic component that needs to be understood is the distance between foster care placements and how distance from a child’s home impacts their outcomes after they leave foster care. These two components have two main neighborhood factors linked to geography. The first is the child’s home ecological characteristics before foster care, and the second is the ecological characteristics of each foster care placement(s). The following research questions (RQ) are used for this dissertation to understand the geographic challenges of children in foster care:

(RQ 1) What are the ecological and population factors that affect the placement stability of a child’s home before they enter foster care, during foster care placements, and during placement changes?

(RQ 2) What foster care placement factors affect a child’s discharge reasons from foster care?

(RQ 3) How does distance to foster care placements affect the outcomes of foster youth aging out of the foster care system?

(RQ 4) Are foster care placement setting types affected by the distance from a child’s home before they enter foster care?

## 3.1 Distance Calculations

This dissertation considers the distance between foster care placements as a contributor to outcomes. The exact address of the child's home and foster care placement(s) was jittered by the providing agency using random perturbation within a 1-mile radius to protect the children and youth's identity in foster care. Random perturbation protects the youth's confidentiality in foster care by shifting the address in a random direction within a designated radius (Zandbergen, 2014).

With the random shift of the address, Euclidean distance provides the most reasonable understanding of the child's experience between foster care placements. The Euclidean distance formula is shown in Equation 3-1 (Alfakih, 2018), where p is the home of the foster child before they entered foster care and q is the location of the foster care placement, and $p_i$ and $q_i$ are the starting points.

**Equation 3-1. Euclidian Distance**

$$d(p, q) \sqrt{\sum_{i=1}^{n} (\ q_i - p_i)^2}$$

In this dissertation, two types of distances are calculated: (1) the distance from the child's home (referred to as distance from home) and (2) the distance from the last foster care placement (referred to as distance from placement). Figure 3-1 depicts what a child with multiple foster care placements could experience.

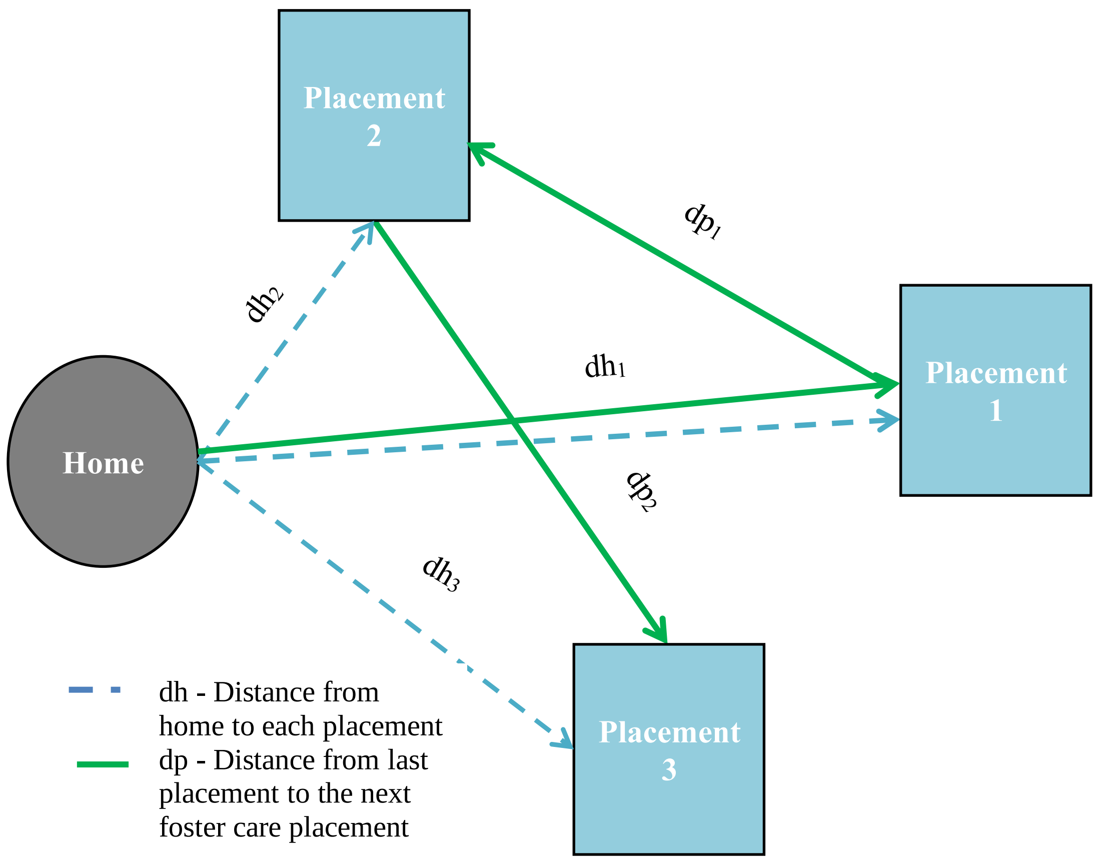


**Figure 3-1. Distance Measurements for Multiple Foster Care Placements**

Figure 3-1 shows two concepts of how distance for a child in foster care can be measured (1) how the distance can be calculated with the child's home as the starting point to all foster care movements, and (2) how the distance can be calculated based on the last foster care placement. An example of the sum and average distance from home is calculated from home to placement 1, home to placement 2, and home to placement 3 is shown with the blue dashed line in Figure 3-1. The sum and average distance from the last placement are based on the distance from the previous placement, which is shown with the solid green line and is calculated from home to placement 1, placement 1 to placement 2, and placement 2 to placement 3 in Figure 3-1.

Table 3-1 lists the calculations for each type of distance measurement. The benefit of calculating the distance using these two concepts shows how distance changes when a child is moved through placements that are further away from home and then closer to home throughout their time in foster care. Equation 3-2 shows the calculation of each placement a child experiences starting from their home to their foster care placement(s) and is represented as $dh_1$. Equation 3-3 is the calculation from each of the last foster care placements that a child was placed at, which is represented as $dp_1$.

Equation 3-4 is based on the cumulative sum of the foster care placements from home to each foster care placement. This equation shows how the sum of each distance to foster care placement accumulates to each foster care placement from home to the foster care placement. Equation 3-5 is similar to Equation 3-4, except the distance begins from the last foster care placement instead of the child's home. Equation 3-6 is the cumulative average of foster care placement from home to the foster care placement(s). Equation 3-7 is the cumulative average of each foster care placement from the last foster care placement.

**Table 3-1. Distance Equations**

**Equation 3-2. Distance from Home**

$$dh = Euclidian\ distance\ from\ home\ to\ placement$$

**Equation 3-3. Distance from Placement**

$$dp = Euclidian\ distance\ from\ last\ placement\ to\ current\ placement$$

**Equation 3-4. Distance Sum to each Placement from Home**

$$d_{home} = \sum_{i=1}^{n} dh_i$$

**Equation 3-5. Distance Sum from each Placement**

$$d_{placement} = \sum_{i=1}^{n} dp_i$$

**Equation 3-6. Distance Average to each Placement from Home**

$$d_{home} = \overline{dh}$$

**Equation 3-7. Distance Average to each Placement from Placement**

$$d_{placement} = \overline{dp}$$

## 3.2 Scale of Analysis

Census tracts and zip codes are the primary geographic units of measurement that ecological studies have used to understand the neighborhood influence on child maltreatment and child welfare (Dorch et al., 2010; Freisthler, 2011; Hillier, 2007; Klein, 2011; Lery, 2009). The benefits of using Census tracts are that the data can be linked to the American Community Survey (ACS) and the decennial Census, which provides detailed population and socioeconomic information and has defined boundaries (U.S. Department of Commerce, Census Bureau, 2017). The average area of a U.S. Census tract is 6 square miles, and the average area of a Census tract in Connecticut is 2.2 square miles. Census tracts are used in this dissertation to define the neighborhood and linked to the 2010 decennial information to capture the youth's neighborhood characteristics in foster care from 2000 to 2015.

## 3.3 Lasso

The Least Absolute Shrinkage and Selection Operator, commonly referred to as Lasso regression, is used when models have multicollinearity. Lasso regressions reduce the model's overfitting through a shrinkage method to select variables. Lasso minimizes the usual sum of squared errors, bound by the sum of the coefficients' absolute values (Tibshirani, 1996). For this dissertation, Lasso regression reduces the number of independent variables used in the models while capturing the neighborhood characteristics to reduce multicollinearity. Lasso regression was selected over Ridge regression and Elastic Net regression because Lasso sets coefficients to zero. When the coefficients are zero or close to zero, it allows for variable selection while ridge and elastic net regression do not. Equation 3-8 is the Lasso regression equation.

**Equation 3-8. Lasso Regression**

$$Goal: Minimize\ Loss\ (\beta_0, \dots\ \beta_m) = \frac{1}{n}\ SSE + \lambda \sum \frac{m}{i = 1}\ |\ \beta_i$$

The Lasso regression results are used in the negative binomial regression and the hierarchal models to reduce the number of population characteristics and socioeconomic variables to define neighborhoods. The population characteristics and socioeconomic factors identified in the Lasso regression results explain the child's neighborhoods before they enter foster care, the neighborhoods of the foster care placements, and the change of neighborhoods using the absolute value. The population characteristics and socioeconomic factors used in the Lasso regression are from the 2010 decennial Census data.

## 3.4 Negative Binomial Regression

Negative binomial regressions have been used to understand the length of stay in different types of foster care settings (James et al., 2012). Negative binomial regression analysis is issued when the dependent variable is a count. Negative binomial regression is selected over other count regression models, such as Poisson regression, when the data are over-dispersed, which occurs when the variance is larger than the mean (Zwilling, 2013), which is particularly common in foster care data. The mean of the $y$ in negative binomial regression is based on the exposure of $t$ and a $k$ regressor set (Zwilling, 2013). Equation 3-9 is the negative binomial regression (Zwilling, 2013).

**Equation 3-9. Negative Binomial Equation**

$$p(y) = P(Y = y) = \frac{\Gamma(y + 1/\alpha)}{\Gamma(\mathrm{y} + 1)\Gamma\left(\frac{1}{\alpha}\right)}\left(\frac{1}{1 + \alpha\mu}\right)^{1/\alpha}\left(\frac{\alpha\mu}{1 + \alpha\mu}\right)^{y}$$

where μ >0 is the mean *Y* and α > 0 is the heterogeneity parameter.

$$\mu = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p$$

where the predictor variables $x_1, x_2, \ldots, x_p$ are given, and the population regression coefficients $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ are to be estimated.

RQ 1 examines the ecological and population factors that affect placement stability. The dependent variables used for RQ 1 are the days a child is in foster care and the number of placements. The independent variables used for this set of research questions include the neighborhood's socioeconomic and population characteristics using Census tract data from the 2010 decennial Census. The Census tract variables that are selected are based on the results of the Lasso regression. RQ 1 examines the child's placement socioeconomic and population characteristics based on (1) the child's home neighborhood before entering foster care, (2) the foster care placement, and (3) the change in characteristics between the child's home and their foster care placement.

## 3.5 Ordinary Least Square Regression

Ordinary Least Square (OLS) regression is used to minimize the sum of the squared errors and can estimate the coefficients to understand the associations between the independent and dependent variables. The OLS model is shown in Equation 3-10 (Hoffmann, 2016). The Breush-Pagan test is used to test for heteroscedasticity. The White's estimator is used when heteroscedasticity is detected since it allows inferences to be made to interpret the model (Hayes & Cai, 2007; White, 1980). White's estimator is often referenced as HC0 and is depicted in Equation 3-11.

**Equation 3-10. OLS Model**

$$y_i = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \varepsilon_i$$

**Equation 3-11. White Estimator**

$$HC0 = (X'X)^{-1}\, X' Diag[e_i^2] X (X'X)^{-1}$$

Ordinary least square regression (OLS) is used to understand the distance from foster care placements for RQ1 due to its continuous response. The same independent variables used in the negative binomial models are also used in the OLS models. The negative binomial regression could not be used for the distance dependent variable since the distance is not counted as the number of foster care placements and days spent in foster care.

## 3.6 Hot Spot Analysis

Getis-Ord Gi$^*$ is the statistical technique that is the most commonly used analysis to test for hot spots. Equation 3-12 shows the Getis-Ord Gi$^*$ statistic (Ord & Getis, 1995).

The Getis-Ord Gi* statistic calculates the z-score and p-values to determine high and low spatial clusters. The larger the z score, the more significant the clustering (Jana & Sar, 2016). If the results show other high values surround a high value, they are in a hot spot, and low values surround by other low values as a cold spot.

**Equation 3-12. Getis-Or Gi* Equation**

(1)

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{s \sqrt{\frac{[n \sum_{j-1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2}{n-1}}}$$

where $x_j$ is the attribute value for feature j, $w_{i,j}$ and the spatial wight between feature i and j, n is equal to the total number of features and:

(2)

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

(3)

$$S = \sqrt[n]{\frac{\sum_{j=1}^{n} x_j^2}{n}} - (\overline{x})^2$$

The Getis-Ord Gi* statistic is used to examine if there are hot spots or cold spots where (1) children with multiple foster care placements live, (2) the time a child spends in foster care, and (3) the total distance children move while in foster care. The hot spots are examined in two ways: the child's home before they enter foster care and the location of the foster care placement. The hot spot and cold spots that are identified indicate where children are located and in possible need of support from DCF based on the number of foster care placements, the time that the children are in foster care, and the distance a child is placed from their home.

The global Moran's *I* is a statistic to measure spatial autocorrelation based on the location and the value. The global Moran's *I* is an inferential statistic used to calculate the z-score and the p-value (Lin & Zhang, 2007). The Moran's *I* value results range from -1 to 1, with 0 meaning that there is no autocorrelation or perfect randomness (Lee & Li, 2017). The global Moran's *I* statistic provides an assessment of overall spatial autocorrelation, while the Getis-Ord Gi* identifies clusters of high or low values.

### 3.7 Welch's T-Test

The means of two groups are compared using a t-test. There are two primary tests to consider when comparing the means of two groups (1) the Student's t-test and (2) Welch's t-test. Welch's t-test or the unequal variance t-test is used to determine if two means are significantly different. The distribution for Welch's t-test is assumed to be normal (Swinscow & Campbell, 1997) and is more robust than Student's t-test, and does not rely on both groups having the same standard deviation (Navarro, 2020). Welch's t-test was selected to see if the hot and cold spots identified by the Getis-Ord Gi* means are significantly different for where (1) children with multiple foster care placements live, (2) the time a child spends in foster care, and (3) the total distance children move while in foster care. The equation of Welsch's t-test is shown in Equation 3-13.

**Equation 3-13. Welch's T-Test Equation**

$$t - stat = \frac{(\bar{x}_A - \bar{x}_B) - (\bar{\mu}_A - \bar{\mu}_B)}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}}$$

## 3.8 Hierarchal Modeling

Hierarchal Linear Models (HLM) are also known as multilevel regression models (MLRM), multilevel models, or hierarchical models (Austin & Merlo, 2017). HLM is used to understand multilevel or nested data within a dataset, which means micro-level (i.e., individual-level) data are associated with the same macro-level group to understand individual characteristics (Kim et al., 2009; Sampson et al., 1997). For example, in this dissertation, HLM analysis is used to determine if children in foster care (micro-level or level 1) are clustered within a neighborhood (i.e., Census Tracts) (macro-level or level 2). HLM is more flexible than ordinary least squares (OLS) regression because of the models' flexibility to test multiple hypotheses (Guo, 2005). The HLM equation is in Appendix B. Hierarchal models can be used with a logistic regression when the outcomes are binary (Austin & Merlo, 2017).

Table 3-2 demonstrates how individual child data is nested within the placement location or the child's home before entering foster care (RQ 2). The child's unique characteristics in hierarchal modeling include characteristics of the child, including race and age, and foster care experience characteristics, including the number of placements, time in foster care, distance from last placement, and distance from home. The dependent variables for RQ 2 examine if the child achieved permanency when they exited foster care. The outcomes associated with permanency include reunification with a parent or guardian, adoption, guardianship, or living with other relatives. The independent variables used for RQ 2 examine the foster care outcomes based on two different level two variables. The first model looks at the child's neighborhood before entering foster care. The second model examines the neighborhood of the foster care placement using the Lasso regression neighborhood indicators.

**Table 3-2. Hierarchal Model Variables**

| Hierarchal Level | Variables |
|---|---|
| Level 1 - Child ID | |
| | Race of child |
| | Age (range 0 – 21) child |
| | Days at placement child |
| | Number of placements |
| | Average distance from home* |
| | Average distance from the last placement** |
| Level 2 - Home ID* or Placement ID** | |
| | Lasso regression results of the neighborhood population and socioeconomic indicators |

* Included only the model based on the home location before a child entered foster care
** Included only in the model based on the location of the foster care placements

## 3.9 Logistic Regression

RQ 3 uses outcomes from the NYTD cohort 1 NYTD survey, which only surveys youth in foster care who are 17 years old. The youth who participated in the NYTD survey is only a small sample, of 1.5 percent, of youth and children represented in this dissertation. The data limitation is based on how the survey is administered and which youth are available for the survey. The NYTD survey is first administered to youth who are 17 years old and asks a series of yes/no questions related to outcomes. Table 3-3 shows the variables used to understand NYTD foster care outcomes.

**Table 3-3. Logistic regression variables**

| | |
|---|---|
| Dependent Variables | NYTD Outcomes Questions (yes/no responses for each question)<br>1. Have you ever been homeless?<br>2. Have you ever referred yourself, or has someone else referred you for an alcohol or drug abuse assessment or counseling?<br>3. Have you ever been confined in a jail, prison, correctional facility, juvenile, or community detention facility in connection with allegedly committing a crime? |
| Independent Variable | Age at removal<br>Race/Ethnicity – Non-Hispanic Black<br>Race/Ethnicity – Non-Hispanic White<br>Race/Ethnicity – Non-Hispanic other<br>Race/Ethnicity – Hispanic<br>Total days in foster care<br>Number of foster care placements<br>Average distance from home<br>Average distance from placement |

Logistic regression is, often referred to as logit regression, is used to model the probability of a discrete outcome; the dependent variable is binary (yes/no). Unlike linear regression, when the result fits a line, logistic regression results are curved to form an s-shape. Logistic regressions are particularly useful in understanding if an event will occur (Cramer, 2003). Logistic regression is used in this dissertation to understand foster care outcomes for older youth in foster care. The NYTD outcomes used in the dissertation are based on whether a youth has experienced incarceration, homelessness, or participated in high-risk behavior.

## 3.10 Multinomial Logit Regression

Multinomial logit regression (MLR) models are used to understand unordered categorical regression variables. MLR models allow for the assessment of multiple nominal dependent variables (Griffiths et al., 2017). When modeling logits, it is assumed that the log-odds follow a linear model. MLR is used for RQ4 to understand placement types. For example, if a child is placed in an institutional placement setting, the child's needs and background require an institutional placement.

MLR examines how distance from home affects placement setting type. The data is examined first by analyzing the effects of distance from the first foster care placement to placement type. The second set of results examines distance from all placement setting types. The categorical dependent variables used in this analysis are the foster family placement types, including (1) foster family home relative, (2) foster family home non-relative, (3) group home, (4) institution, (5) supervised independent living, and (6) trial home visit. The reference group in both sets of analyses is foster family home non-relative. The first model only examines the distance from the home to the first foster care placement and excludes trial home visits from the analysis since it occurs less than 1 percent of the time in the data, and the distance could not be calculated since the location was often the same as the home address.

Distance from home is the only distance measurement that could be used in the first model since it is only based on the first move that a child experiences. The second model includes each type of foster care placement, the total distance from home, and the total distance from each placement. Table 3-4 lists the dependent and independent variables used in the multinomial regression to determine the effects of the distance to foster care placement type. Variables are assessed for multicollinearity.

**Table 3-4. Multinomial Logistic Regression Variables**

| | |
|---|---|
| Dependent Variables | Foster family home non-relative |
| | Foster family home relative |
| | Group home |
| | Institution |
| | Supervised independent living |
| | Trial home visit* |
| Independent Variable | Age at removal |
| | Race/Ethnicity – Non-Hispanic Black |
| | Race/Ethnicity – Non-Hispanic White |
| | Race/Ethnicity – Non-Hispanic other |
| | Race/Ethnicity – Hispanic |
| | Total days in foster care |
| | Number of foster care placements |
| | Distance from home ** |
| | Average distance from home* |
| | Average distance from placement* |

**Exclude from the model that only examines the first foster care placement*
***Excluded from the model that looks at each foster care placement*

## 3.11 Summary

This dissertation investigates how distance from home and between foster care placements impacts foster children. The methods presented here answer the research questions regarding the impact of geographic factors on foster children's experiences. The breadth of statistical techniques is intended to provide a complete view of a child's experience through multiple foster care placements. This view should help practitioners understand the importance of the neighborhood of the child's home before they enter foster care, the neighborhood characteristics of the foster care placement(s), and the neighborhood changes at each foster care placement.

# 4. DATA

The Connecticut (CT) Department of Children and Families (DCF) provided foster care placement data from 2000 to 2015. Institutional Review Board (IRB) approval for this research was given by the George Mason University IRB and the Connecticut DCF IRB (DCF IRB #2016-07). The information provided by Connecticut DCF included data on 44,648 children who were in foster care from 2000 to 2015. Information about the children included the age at foster care entry and the child's race. Information about the child's foster care experience included: the type of foster care placement, entry and exit date into foster care, placement id, home id, and federal discharge reason. An additional outcome measure provided by DCF included the survey responses of cohort one, year one, NYTD survey of youth who have exited foster care.

Connecticut DCF also provided the placement and the home address of the child. The address data were jittered to mask the exact location of the child's placement or home before being removed from DCF offices. The data were masked by creating a one-mile buffer around the placement and home and jittering a new point within the buffer within the home or placement Census tract. This data measure was used to ensure that the child's exact location and placement were protected.

This dissertation includes the 22,456 children who entered and exited foster care in Connecticut from 2000 to 2015. Children excluded from this dissertation experienced either having (1) an out-of-state placement and were no longer in the care of Connecticut's DCF or (2) a foster care placement status as a runaway. When a child experiences an out-of-state foster care placement, they are typically placed with a family member, kin, or specialized care that cannot be achieved within their jurisdiction (Connecticut Department of Children and Families, 2020). When a child has a foster care placement classified as a runaway, the child left their home or the facility they were living in without authorization (U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2020). Children with a runaway status were excluded from this dissertation because their exact location could not be geocoded and counted in the distance calculations.

## 4.1 Child Characteristics

### 4.1.1 Age at Foster Care Entry

The average age that a child entered foster care in Connecticut was 7.5 years old. Figure 4-1 shows the child's age when they first entered foster care in Connecticut from 2000 to 2015. Fifteen percent of the children who first entered foster care were less than a year old. There is a steady decrease in the age when a child first enters foster care for children from one to twelve years old. This trend changes near adolescence, with an increase in children entering foster care for the first time at age 12. Nearly 15 percent of the children who enter foster care from 2000 to 2015 are 15 or 16 years old. Less than two percent of the children who enter foster care are 18 years or older. Connecticut, like many states, allows children to remain in foster care until they are 21 years old through an extended foster care program.

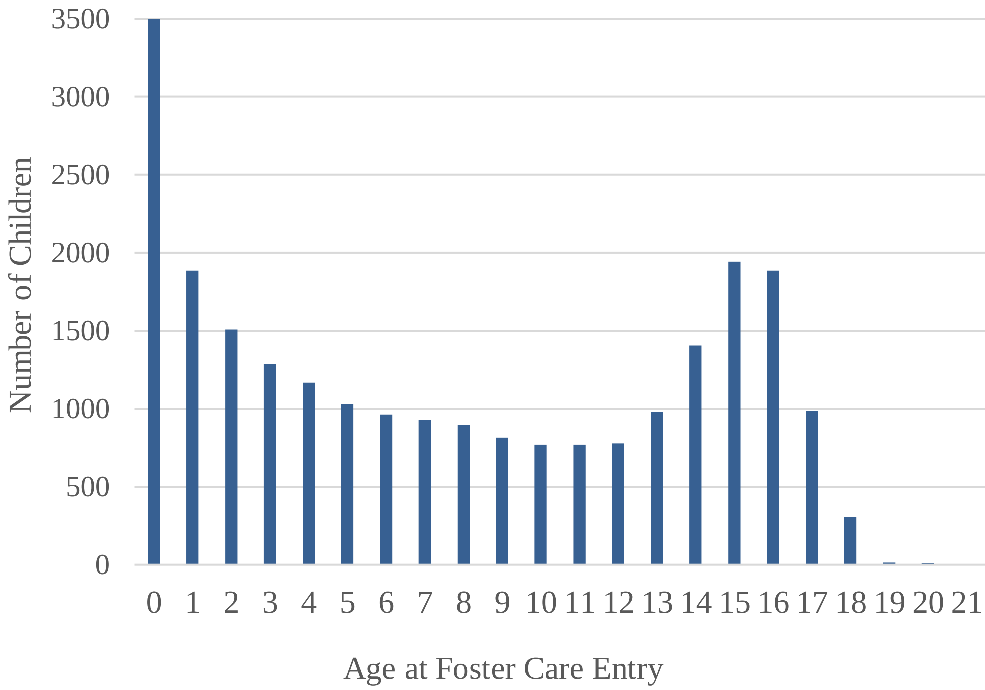

**Figure 4-1. Age at Foster Care Entry in Connecticut**

### 4.1.2 Racial composition

The racial composition of children in foster care in Connecticut from 2000 to 2015 was diversely representative. Non-Hispanic, White children represent the most substantial racial-ethnic composition, with 35 percent, followed by non-Hispanic Black, representing 28 percent of Connecticut's foster care population. Thirty percent of the children in the Connecticut foster care system have a Hispanic origin. Figure 4-2 shows the racial-ethnic composition of the Connecticut foster care system youth. Hispanic, American Indian, or Alaskan Native; Hispanic; Asian, Hispanic; Native Hawaiian / other Pacific Islander; Hispanic, Non-Hispanic, American Indian, or Alaskan Native; Non-Hispanic, Asian; Non-Hispanic, Native Hawaiian / other Pacific Islander; and Non-Hispanic, and unable to determine or not reported categories were one percent of the children in foster care and were collapsed into the other category in Figure 4-2.

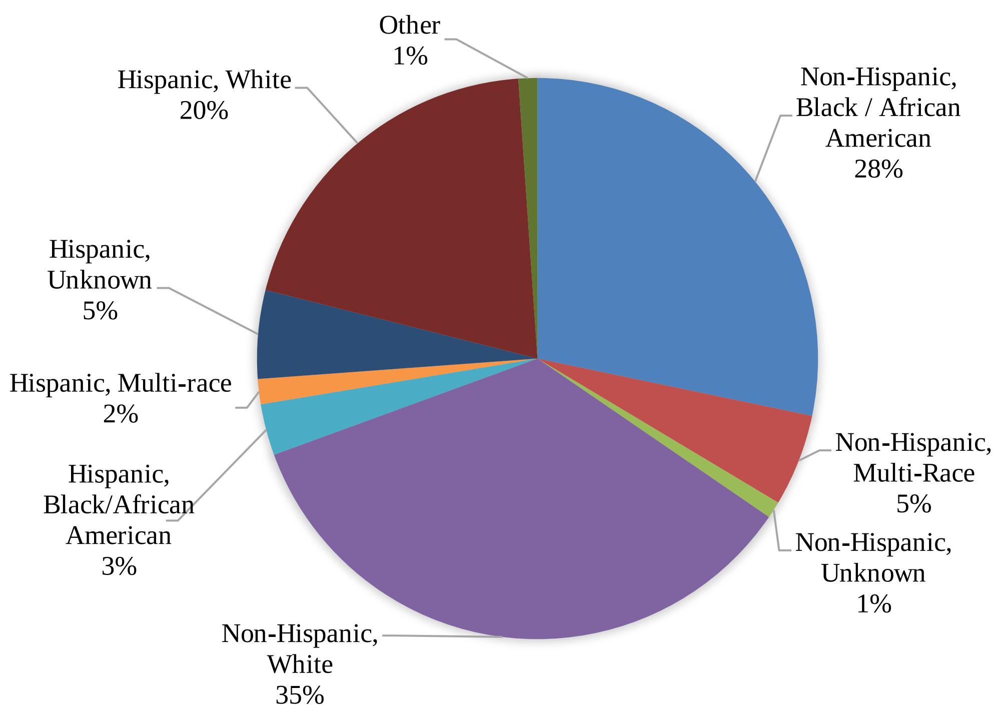


**Figure 4-2. Racial/Ethnic Composition of Children in Foster Care in Connecticut**

## 4.2 Foster Care Placement

### 4.2.1 Number of Foster Care Placements

In Connecticut, there were 59,160 foster care placements for 22,456 children. The average number of foster care placements was 2.6 from 2000 to 2015. A third of the children in foster care, 32.7 percent, experienced one foster care placement. The majority, 95.4 percent of the children in Connecticut, had fewer than six foster care placements. Less than one percent of the youth in foster care experienced ten or more foster care placements. Table 4-1 shows the count of how many placements a child in foster care had, the frequency of the placements, and the cumulative frequency of the total number of foster care placements.

**Table 4-1. Number of Foster Care Placements in Connecticut**

| Number of Children with Placement Count | Count | Frequency | Cumulative Frequency |
|---|---|---|---|
| n = 22,456 | | | |
| 1 Placement | 7,349 | 32.73% | 32.73% |
| 2 Placements | 6,235 | 27.77% | 60.49% |
| 3 Placements | 3,810 | 16.97% | 77.46% |
| 4 Placements | 2,138 | 9.52% | 86.98% |
| 5 Placements | 1,225 | 5.46% | 92.43% |
| 6 Placements | 655 | 2.92% | 95.35% |
| 7 Placements | 360 | 1.60% | 96.95% |
| 8 Placements | 263 | 1.17% | 98.13% |
| 9 Placements | 140 | 0.62% | 98.75% |
| 10 Placements | 95 | 0.42% | 99.17% |
| 11 Placements | 62 | 0.28% | 99.45% |
| 12 Placements | 40 | 0.18% | 99.63% |
| 13 Placements | 20 | 0.09% | 99.71% |
| 14 Placements | 17 | 0.08% | 99.79% |
| 15 Placements | 16 | 0.07% | 99.86% |
| 16 Placements | 8 | 0.04% | 99.90% |
| 17 Placements | 6 | 0.03% | 99.92% |
| 18 Placements | 5 | 0.02% | 99.95% |
| 19 Placements | 5 | 0.02% | 99.97% |
| 20 Placements | 1 | 0.00% | 99.97% |
| 21 Placements | 3 | 0.01% | 99.99% |
| 24 Placements | 3 | 0.01% | 100.00% |

### 4.2.2 Days in Foster Care

The average time a child was in foster care was 2,036 days, approximately 5.6 years, with the average time at a foster care placement lasting 611 days, approximately 1.6 years. Children who only had one foster care placement averaged 289 days in foster care and spent a longer time at their only foster care placement than children with multiple foster care placements. Four percent of the children in foster care had one foster care placement that lasted one day. Fourteen percent of the foster care children who had one foster care placement were in foster care for less than a week (seven days). Children with two foster care placements, on average, spent more time at their first foster care placement than children with three or more foster care placements. Children with 19 or more foster care placements spent the shortest amount of time at their first foster care placement, with an average of 72 days (just over two months).

The stacked bar graph in Figure 4-3 shows the average length of time in foster care at each foster care placement. Figure 4-3 shows that the more foster care placements a child has, the longer they are in foster care. There are a few exceptions, with children who have 17 and 19 foster care placements having spent more time in foster care than children with more than 20 foster care placements. This number of children represents a small percentage of the total number of children in foster care, with only seven children having more than 20 foster care placements in the data used for this dissertation.

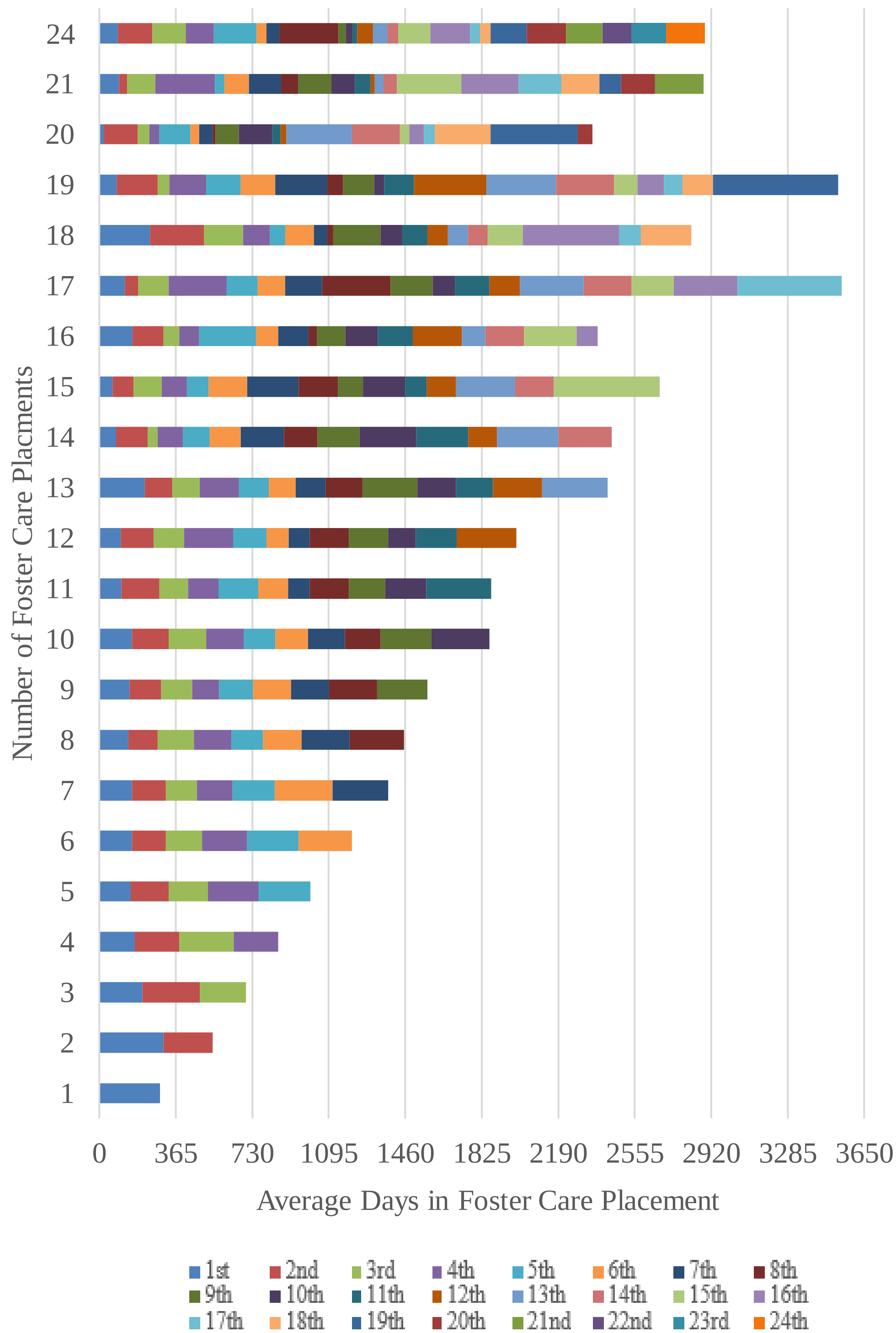


**Figure 4-3. Time and Number of Foster Care Placements in Connecticut**

### 4.2.3 Federal Placement Type

The 22,456 children in foster care from 2000 to 2015 experienced 59,160 foster care placements. Table 4-2 shows that the majority, 54.6 percent, of the children who were in foster care in Connecticut were placed with non-relative foster families, and 19.4 percent of the foster care placements are with a relative in a foster family home. Trial home visits and institution foster care placements represent approximately 20 percent of all foster care placements combined. Less than one percent of the children in foster care have a foster care placement that is a supervised independent living placement.

**Table 4-2. Foster Care Placement Types in Connecticut**

| Federal Placement Type<br>n = 59,160 | Frequency | Count |
|---|---|---|
| Foster Family Home (Non-Relative) | 54.6% | 32,318 |
| Foster Family Home (Relative) | 19.4% | 11,496 |
| Group Home | 5.9% | 3,475 |
| Institution | 10.3% | 6,091 |
| Supervised Independent Living | 0.6% | 345 |
| Trial Home Visit | 9.2% | 5,435 |

With 68 percent of the children in foster care experiencing more than one foster care placement, the type of foster care placement can change with each placement setting. Figure 4-4 shows the first five foster care placements that children in Connecticut experienced and how the placement type changes after each foster care placement. Sixteen percent of the children experienced one foster care placement at a non-relative foster family home. Ten percent of the children experienced one foster care placement at a relative foster family home. Eight percent of the children's first and second foster care placements are at foster family non-relative placements. Five percent of the children who experience three foster care placements are foster family non-relatives.

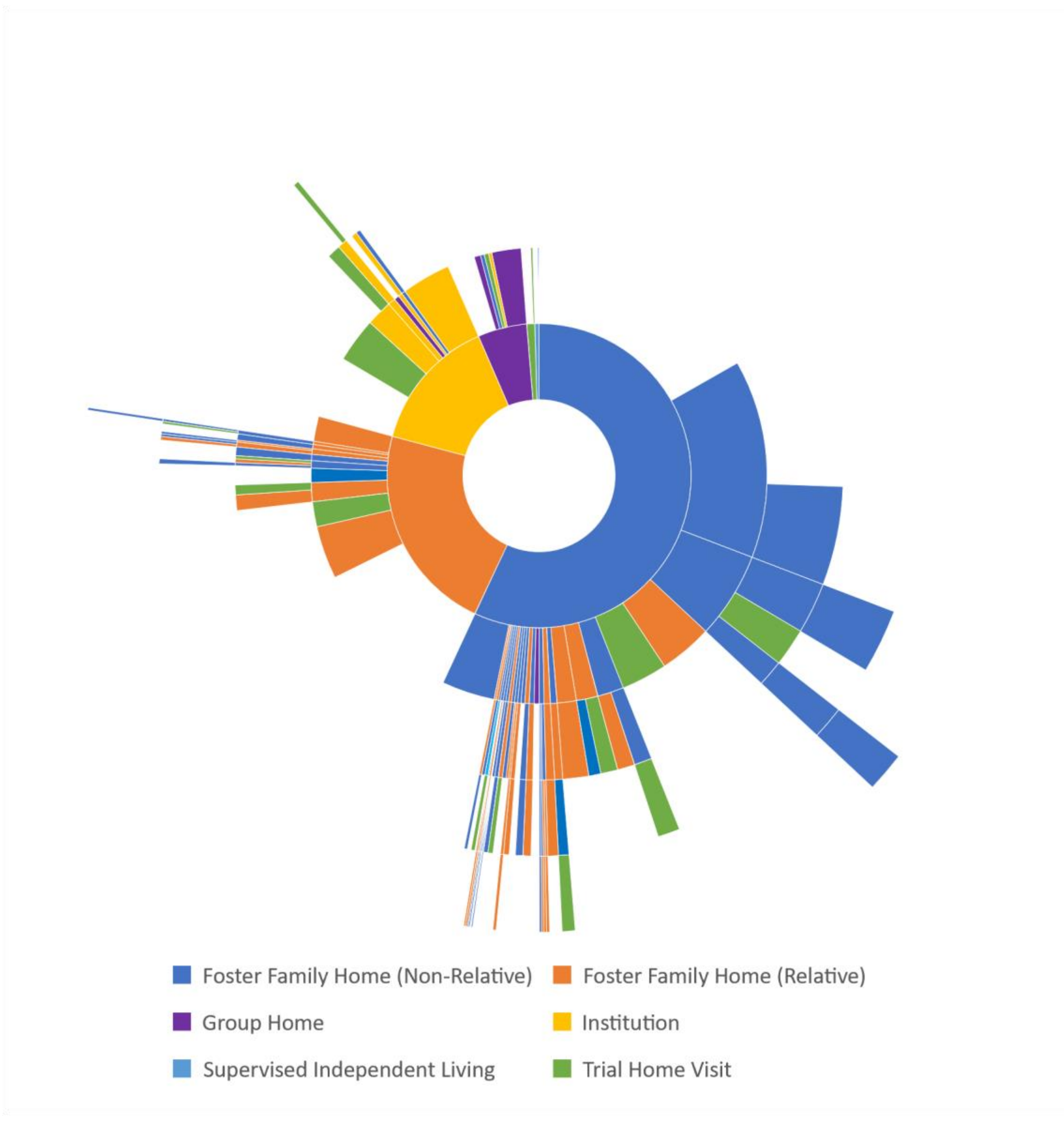


**Figure 4-4. Number of Placements by Foster Care Placement Type in Connecticut**

### 4.2.4 Distance to Placement

Distance between foster care placements is calculated in two different ways. The first distance calculation for multiple foster care placements is the distance from home, which is calculated from home to foster care placement 1, home to foster care placement 2, home to foster care placement three, etc. The second distance calculation is the distance from placement which is calculated from home to foster care placement one and then the distance from foster care placement 1 to foster care placement 2, the distance from foster care placement 2 to foster care placement 3, etc. Table 4-3 shows the average distance from home that children in foster care experience by age, race, time in care, number of foster care placements, and placement type.

**Table 4-3. Average Distance to Foster Care Placements in Connecticut**

| | Average distance from home to all placements in miles | Average distance of all placements in miles from the last placement | t-test significance |
|---|---|---|---|
| **Race/Ethnicity** | | | |
| Non-Hispanic Black/African American | 25.8 | 7.4 | *** |
| Non-Hispanic White | 30.5 | 9.0 | *** |
| Hispanic | 27.0 | 8.4 | *** |
| **Age** | | | |
| 0 to 4 years old | 29.0 | 6.2 | *** |
| 5 to 13 years old | 28.0 | 7.8 | *** |
| 14 to 21 years old | 25.6 | 11.4 | *** |
| **Time in care** | | | |
| Less than a year (365 days) | 27.6 | 7.7 | *** |
| More than a year (366 or more days) | 28.5 | 7.1 | *** |
| **Number of foster care placements** | | | |
| 1 foster care placement | 30.0 | 0.0 | *** |
| 2 foster care placements | 26.2 | 7.1 | *** |
| 3 foster care placements | 27.7 | 8.3 | *** |
| 4 foster care placements | 28.3 | 9.7 | *** |
| 5 foster care placements | 27.5 | 10.3 | *** |
| 6 or more foster care placements | 28.3 | 11.4 | *** |
| **Placement type** | | | |
| Foster Family Home (Non-Relative) | 31.1 | 5.3 | *** |
| Foster Family Home (Relative) | 30.1 | 4.4 | *** |
| Group Home | 30.4 | 13.3 | *** |
| Institution | 28.0 | 9.2 | *** |
| Supervised Independent Living | 28.6 | 8.6 | *** |
| Trial Home Visit | 1.2 | 28.1 | *** |
| **Federal discharge reason** | | | |
| Positive | 27.5 | 7.8 | *** |
| Negative | 28.6 | 9.1 | *** |

*** 0.001, **0.01, *0.05

Table 4-3 provides a set of descriptive statistics for the average distance for children across all of their placements from their home and the average distance from the last foster care placement to the subsequent placement across a number of child and neighborhood characteristics. The third column provides a measurement of the level of significance for the t-test between the two distance measures for the relevant child or neighborhood characteristics, which were all found to be significant.

Census tract size is important to understand the impact of distance and Census tracts since Census tracts serve as a proxy for neighborhoods. The average area of a U.S. Census tract is 6.0 square miles, and the average size of a Census tract in Connecticut is 2.2 square miles. Figure 4-5 shows the types of foster care placements in the same Census tract of the home Census tract of the child before they entered foster care. Six percent of the placements that are the same as the child's home before they entered foster care are trial home visits which means that the child's family had remained in that Census tract since the child entered foster care. The number of children who remained in the same Census tract as their home Census tract or neighborhood while in foster care was 5.7 percent (3,357 placements) of the total number of children in foster care.

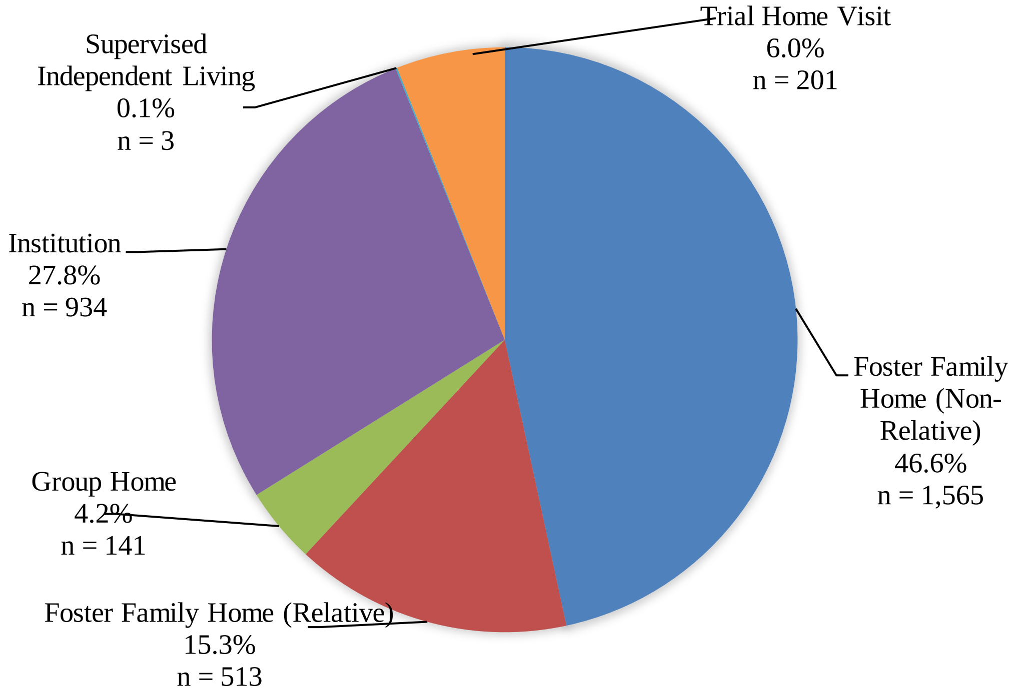


**Figure 4-5. Children's Placement Type that is in the same Home Census Tract**

One hundred and fifty-eight children who only had one foster care placement remained in the same Census tract as their only foster care placement; this represents less than one percent of all foster care placements. One hundred and forty-nine children were placed in a trial home foster care placement as their only foster care placement. The remaining nine foster care placements for one foster care placement in the same Census tracts included one foster family home (non-relative), four foster family homes (relative), one group home, and three institutions. No children with multiple foster care placements remained in the same Census tract for their entire time in foster care.

## 4.4.1 Foster Care Outcomes

### *4.4.1.1 Federal Discharge Reasons*

When children leave foster care, the foster care agency intends to find a permanent housing solution for those children, so they will not have to return to foster care. When a child exits foster care, DCF categorizes their exit based on the federal discharge reason (FDR). FDRs are classified into two groups (1) a child achieving permanency or (2) a child did not achieve permanency. A child can achieve permanency through exiting foster care by being adopted, reunified with their family, living with a guardian, or living with another family member. A child might not achieve permanency when they exit foster care due to a transfer to another agency, run away status, death, missing or unknown reason, or emancipation. Table 4-4 shows the FDRs for children in Connecticut experienced from 2000 to 2015. The FDRs in Table 4-4 are based on the last FDR a child experienced. Of the children in foster care, the majority, 79 percent, achieved a positive permanency outcome. Twenty-one percent of the children did not achieve permanency, a negative outcome.

**Table 4-4. Federal Discharge Reasons from Foster Care in Connecticut**

| Federal Discharge Reason (FDR)<br>n = 22,456 | Frequency | Percent |
|---|---|---|
| **Achieved Permanency** | **18,600** | **79.0%** |
| Adoption | 4,786 | 20.3% |
| Guardianship | 3,108 | 13.2% |
| Living with other relative(s) | 697 | 3.0% |
| Reunification with parent(s) or primary caretaker(s) | 10,009 | 42.5% |
| **Did not Achieve Permanency** | **4,931** | **21.0%** |
| Emancipation | 2,453 | 10.4% |
| Missing or unknown, runaway, death of a child | 2,165 | 9.2% |
| Transfer to another agency | 313 | 1.3% |

A FDR is associated with a child every time the youth exits the foster care system; each time a child enters the foster care system is referred to as an episode. A small percentage of children experience multiple FDRs because of an unsuccessful adoption, guardianship, reunification with their family, or another reason. In this dissertation, 10.3 percent of youths had more than one foster care episode. Ninety-eight percent of the youth who had multiple FDRs had two or three FDRs. Figure 4-6 is a Sankey diagram that shows the path of children who had two or three federal discharge reasons.

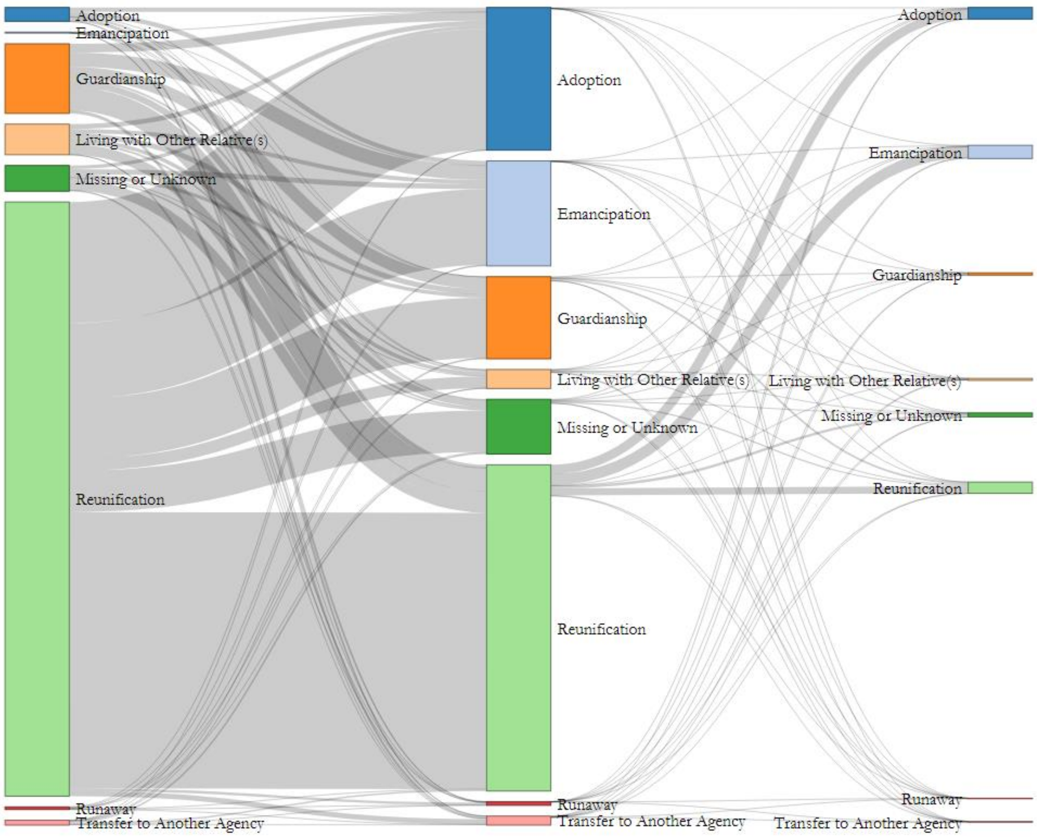


**Figure 4-6. Multiple Federal Discharge Reasons**

Figure 4-6 excluded the two percent of the children who had four or more FDRs. Of the children who had four or more, twenty-three children had four FDRs. Two children had five foster care episodes, both of which had ten foster care placements. For both these children, that FDR, for each foster care episode, was reunification with parents. One child in this dataset had six foster care episodes and eight foster care placements, each of these episodes ended was an FDR of reunification with parents.

#### *4.4.1.2 National Youth in Transition Database (NYTD)*

The second set of outcomes used to understand placement stability for youth in foster care is the NYTD Survey cohort 1, 17-year-olds. The NYTD survey population is a subset of the entire population in this dataset. This subset is based on youth who were 17 in 2011 when the survey was conducted. The survey design and implementation are based on federal regulation 45 CFR 1356.83(g)(34). The NYTD data are based on (1) federally regulated survey questions and (2) federally regulated survey opportunities. At the time of this dissertation's data collection, only one cohort of NYTD data was available. The resulting dataset is the 339 youth who were 17 when the cohort one dataset was administered, which is 1.5 percent of the children and youth in the dataset provided by the Connecticut DCF.

This research focuses on NYTD questions related to homelessness, risky behavior, and incarceration. The survey questions regarding positive connection to an adult, employment, and education were not included in this research since the survey cohort only includes youth who are 17 years old, which typically means the youth are still in school. Table 4-5 is the Connecticut DCF NYTD survey questions used in this dissertation. The complete NYTD survey can be found in Appendix C.

**Table 4-5. NYTD Survey Question**

| Category | Question Number | Connecticut Department of Children and Families NYTD Youth Outcome Survey questions |
|---|---|---|
| **Homelessness** | 10 | Have you ever been homeless? |
| **Risky Behavior** | 11 | Have you ever referred yourself, or has someone else referred you for an alcohol or drug abuse assessment or counseling? |
| **Incarceration** | 12 | Have you ever been confined in a jail, prison, correctional facility, juvenile, or community detention facility in connection with allegedly committing a crime? |

During this data analysis period, 339 or 1.6 percent of the youth were eligible for the NYTD survey. Of the eligible youth, 91.4 percent agreed to participate in the survey. Table 4-6 shows that amongst the youth who were surveyed, less than a quarter of the youth who responded to the survey had experienced homelessness, risky behavior, or incarceration.

**Table 4-6. NYTD Survey Responses**

| n = 337 | Yes | Percent of survey respondents who answered yes | No | Percent of survey respondents who answered no |
|---|---|---|---|---|
| Homelessness | 38 | 11.3% | 299 | 88.7% |
| Risky Behavior | 86 | 25.5% | 251 | 74.5% |
| Incarceration | 73 | 21.7% | 264 | 78.3% |

The national results of the NYTD survey found higher response rates than in Connecticut. According to the *Highlights from the NYTD Survey: Outcomes reported by youth at ages 17, 19, and 21 (Cohort1),* found that for youth who completed all three waves of the NYTD survey, 43 percent had experienced homelessness. The national-level responses to NYTD also reported that 50 percent of the youth had reported risky behavior, which focuses on outcomes related to substance abuse, incarceration, or pregnant and parenting (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau., 2012).

## **4.3 Connecticut Geography**

Connecticut is located in the Northeast part of the U.S., with a population of 3.5 million (U.S. Department of Commerce, Census Bureau, 2020b). Figure 4-7 shows the location of Connecticut and its eight counties. The Census defines Litchfield, New Haven, and Fairfield Counties as part of the New York City Combined Statistical Area (CSA) Metropolitan / Micropolitan Statistical Area. CSAs are associated with urban clusters and are socially and economically linked to the urbanized area (U.S. Department of Commerce, Census Bureau, 2020a).

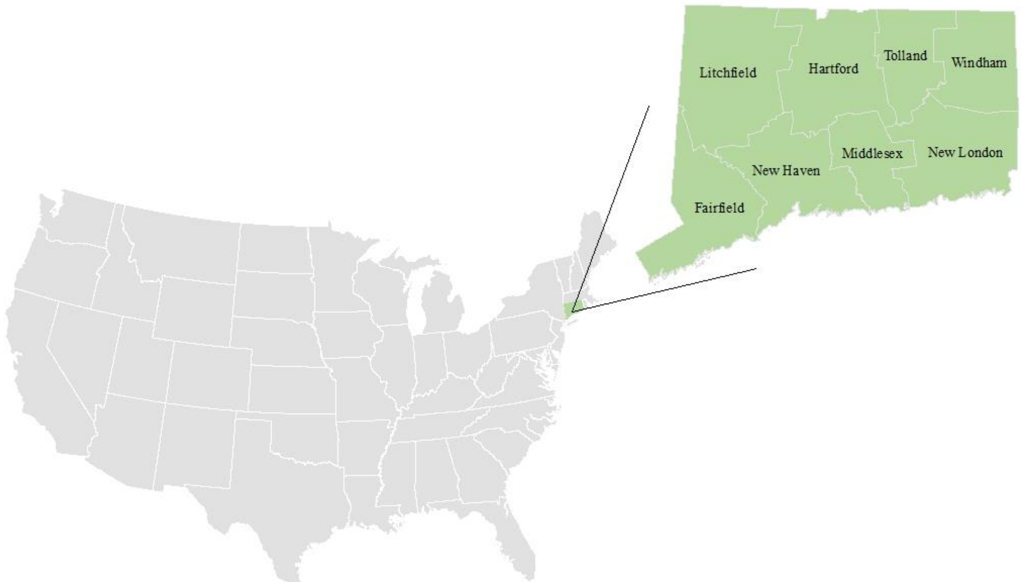


**Figure 4-7. Map of the United States**

Table 4-7 shows the 2010 county population in Connecticut (U.S. Department of Commerce, Census Bureau, 2012) and the counties children lived in before they entered foster care, and the count of counties where children were placed during their time in foster care. Fairfield County is the most populist county with over 940,000 residents, and Windham County is the least populist with just over 117,000 residents (Connecticut Department of Health and Human Services, 2020).

**Table 4-7. Connecticut Foster Care Population by County**

| County | 2010 population | Count of children's home before foster children n = 22,456 | Count of children's placements during foster care n =59,160 |
|---|---|---|---|
| Fairfield County | 916,829 | 3,203 | 8,265 |
| Hartford County | 894,014 | 7,342 | 18,302 |
| Litchfield Count | 189,927 | 901 | 2,903 |
| Middlesex County | 165,676 | 558 | 4,125 |
| New Haven County | 862,477 | 6,371 | 15,050 |
| New London County | 574,055 | 2,464 | 6,156 |
| Tolland County | 152,691 | 525 | 1,522 |
| Windham County | 118,428 | 1,090 | 2,831 |

Figure 4-8 shows that 32.7 percent of the children entering foster care from 2000 to 2015 were from Hartford County. The fewest number of children who entered foster care were from Tolland County and Middlesex County. The county with the most foster care placements from 2000 to 2015 was Hartford County, with 30.9 percent of all the foster care placements. Tolland County and Windham County have the fewest foster care placements.

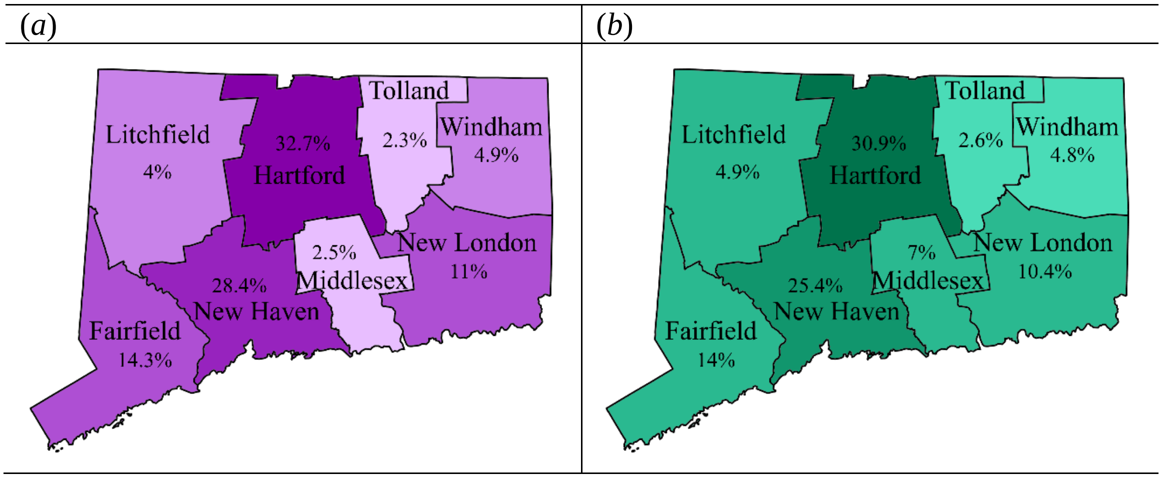


**Figure 4-8. Foster Care Entries and Placements in Connecticut**
(a) County map of the location of the child's home before they entered foster care
(b) County map of the location of the child's foster care placements

Table 4-8 lists socioeconomic and population characteristics for the U.S. and Connecticut (U.S. Department of Commerce, Census Bureau, 2020b). Compared to the U.S., Connecticut has a greater percentage of the population that is non-Hispanic White and a smaller percentage of the population that is Hispanic or non-Hispanic Black or African American. The median household income and the percent of the population with a bachelor's degree or higher are greater in Connecticut than in the rest of the U.S. The U.S. has a similar population under 18, with only a two percent difference between the U.S. and Connecticut.

**Table 4-8. Census Characteristics of Connecticut**

| | U.S. | Connecticut |
|---|---|---|
| Percent female head of household | 17.8% | 12.9% |
| Median household income | $60,293 | $76,106 |
| Percent poverty | 10.5% | 10.0% |
| Percent of households that rent | 14.2% | 3.2% |
| Percent of unemployed | 9.6% | 9.1% |
| Percent under 18 | 22.3% | 20.4% |
| Percent Hispanic | 18.5% | 16.9% |
| Percent non-Hispanic White | 60.1% | 65.9% |
| Percent non-Hispanic Black/African American | 18.5% | 16.9% |
| Percent of high school education | 87.7% | 90.5% |
| Percent of college education | 31.5% | 38.9% |
| Population per Square mile | 87.4 | 738.1 |

The variables in Table 4-8 were selected for this dissertation because they are commonly used to understand the geographic patterns of child maltreatment and social work. These variables are used in a correlation matrix and LASSO regression to help determine which variables would be included in the analysis and to reduce multicollinearity within the models. Table 4-9 lists the minimum, the maximum, the mean, and the standard deviation of the Census tracts that have the child's home before they entered foster care and the location of the foster care placements using the 2010 decennial Census information. Generally, the placement's mean is lower in socioeconomic indicators than the child's home before entering foster care. However, the mean placement Census tracts are 13 percent greater for non-Hispanic White, which is the most notable change in racial composition

**Table 4-9. Census Characteristics of Connecticut**

| | Home Before Foster Care | | | | Foster Care Placements | | | |
|---|---|---|---|---|---|---|---|---|
| Census tract variables | Min | Max | Mean | S.D. | Min | Max | Mean | S.D. |
| Percent female head of household | 0 | 100% | 21.1% | 11.8% | 0 | 100% | 16.9% | 10.5% |
| Median household income | 7,545 | 250,000 | $51,224 | $25,635 | 7,545 | 250,000 | $66,281 | $29,007 |
| Percent of households that rent | 0 | 100% | 55.9% | 26.5% | 1 | 100% | 41.1% | 26.6% |
| Percent of unemployed | 0 | 24.8% | 7.3% | 3.8% | 0 | 24.8% | 5.9% | 3.3% |
| Percent under 18 | 0 | 47.2% | 22.8% | 6.6% | 0.7% | 47.2% | 21.4% | 5.6% |
| Percent Hispanic | 0 | 85.3% | 29.6% | 21.4% | 0 | 85.3% | 20.5% | 19.3% |
| Percent non-Hispanic White | 0 | 97.9% | 44.2% | 29.9% | 0 | 97.8% | 57.0% | 30.4% |
| Percent non-Hispanic Black or African American | 0 | 0 | 94.5% | 94.5% | 19.8% | 16.1% | 19.3% | 19.1% |
| Percent of high school education | 4.1% | 2.9% | 56.6% | 56.6% | 33.2% | 31.5% | 8.1% | 8.5% |
| Percent of college education | 0 | 0 | 45.1% | 51.6% | 13.6% | 16.7% | 7.9% | 7.9% |
| Percent urban | 0 | 0 | 100% | 100% | 89.3% | 78.9% | 25.2% | 34.8% |

Table 4-10 shows the results of the correlation matrix of commonly used Census tract data in social work literature. The variables that show no correlation in the correlation matrix include the percent of the population under 18, percent of the urban area, percent with high school education, percent non-Hispanic Black, and percent unemployed. The highly negatively correlated variables include non-Hispanic white, median household income, and college education. The highly positively correlated variables include the percent of the population on public assistance, the percent of households that rent, and the percent of households below poverty.

**Table 4-10. Correlation Matrix of Neighborhood Characteristics**

| | Percent Non-Hispanic White | Percent College Education | Median Household Income | Percent Under 18 | Percent Urban | Percent High School Education | Percent Non-Hispanic Black | Percent Unemployed | Percent Female Head of Household | Percent Hispanic | Percent Public Assistance | Percent Households that Rent | Percent Below Poverty |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Percent Non-Hispanic White | 1.00 | | | | | | | | | | | | |
| Percent College Education | 0.61 | 1.00 | | | | | | | | | | | |
| Median Household Income | 0.60 | 0.77 | 1.00 | | | | | | | | | | |
| Percent Under 18 | -0.30 | -0.06 | 0.09 | 1.00 | | | | | | | | | |
| Percent Urban | -0.46 | -0.21 | -0.24 | 0.08 | 1.00 | | | | | | | | |
| Percent High School Education | -0.41 | -0.83 | -0.70 | -0.03 | 0.16 | 1.00 | | | | | | | |
| Percent Non-Hispanic Black | -0.82 | -0.49 | -0.46 | 0.19 | 0.33 | 0.34 | 1.00 | | | | | | |
| Percent Unemployed | -0.69 | -0.56 | -0.53 | 0.37 | 0.27 | 0.42 | 0.56 | 1.00 | | | | | |
| Percent Female Head of Household | -0.77 | -0.65 | -0.60 | 0.41 | 0.33 | 0.49 | 0.65 | 0.70 | 1.00 | | | | |
| Percent Hispanic | -0.86 | -0.62 | -0.57 | 0.36 | 0.39 | 0.43 | 0.47 | 0.66 | 0.72 | 1.00 | | | |
| Percent Public Assistance | -0.60 | -0.59 | -0.50 | 0.24 | 0.24 | 0.42 | 0.47 | 0.58 | 0.63 | 0.60 | 1.00 | | |
| Percent Households that Rent | -0.77 | -0.58 | -0.70 | 0.10 | 0.40 | 0.39 | 0.55 | 0.58 | 0.64 | 0.73 | 0.65 | 1.00 | |
| Percent Below Poverty | -0.71 | -0.61 | -0.58 | 0.23 | 0.30 | 0.38 | 0.50 | 0.65 | 0.67 | 0.72 | 0.73 | 0.81 | 1.00 |

The last way this dissertation understands the impact of the population and socioeconomic factors on children in foster care is by calculating the absolute value between the home Census tract and the placement Census tract(s). The Census variables' absolute value was calculated for this dissertation using two approaches (1) the absolute value between the home Census tract and the first placement Census tract, and (2) the absolute value between the home Census tract and all foster care placements Census tracts.

Figure 4-9 shows the absolute value change of the percent of the population that is Hispanic and non-Hispanic Black, as well as the percent of the population on public assistance, percent of families below poverty, percent of the population under the age of 18, and the percent of the Census tract that is urban in a box plot for the first foster care placement and for all foster care placements. The yellow dot on the box plot in Figure 4-9 represents the average percent change of the listed Census tract characteristics.

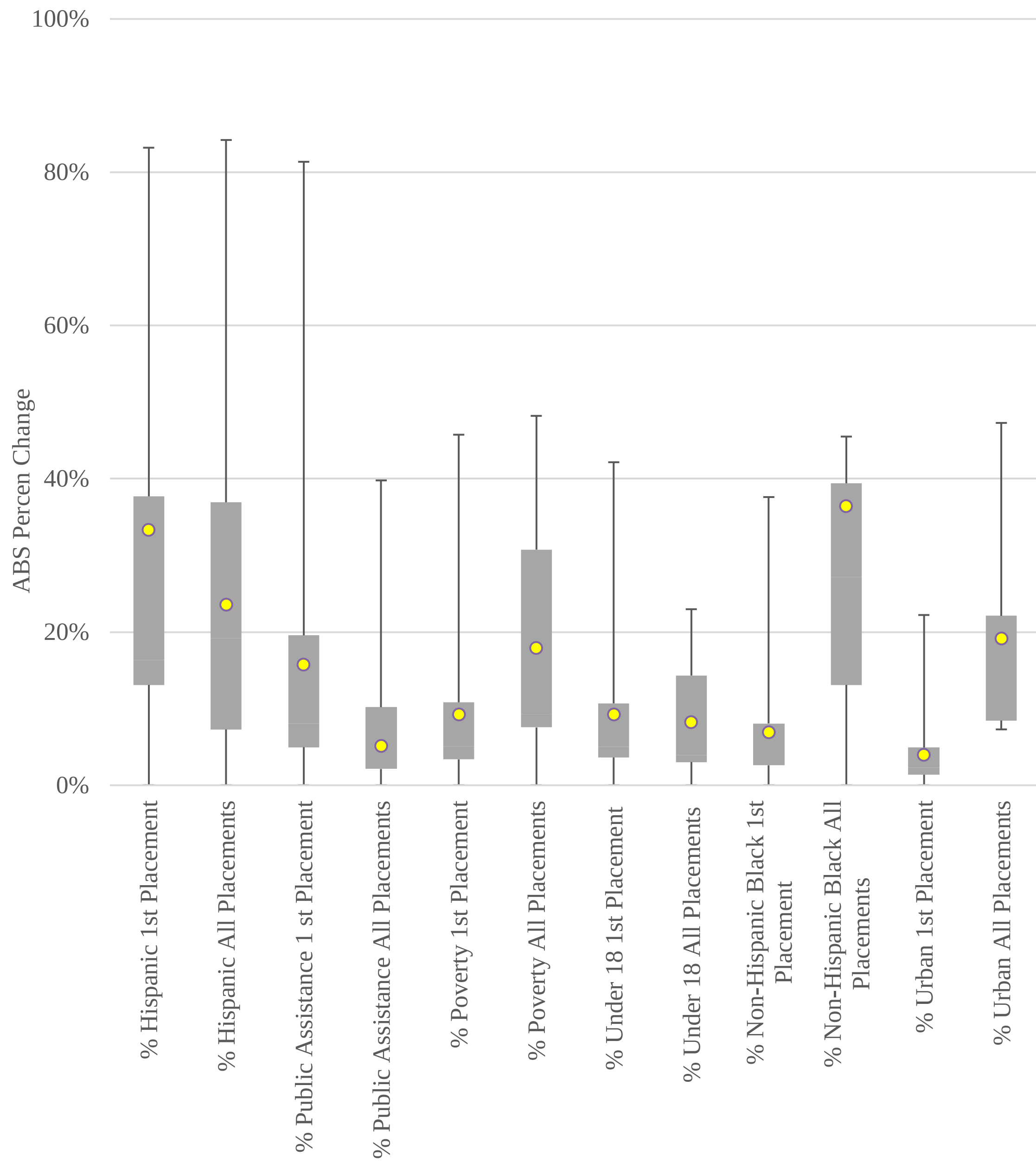


**Figure 4-9. Absolute Value Change of Foster Care Placements**

Figure 4-9 shows the greatest socioeconomic and population differences between Census tracts for the first foster care placement and all foster care placements for non-Hispanic Black. The average change of Census tract for the first foster care placement is 6.9 percent, and for all foster care placements is 36.4 percent. The second greatest difference in socioeconomic and population differences between Census tracts for the first foster care placement and all foster care placements is the percent that a Census tract is urban. The average urban change in the Census tract for the first foster care placement is 3.9 percent, and for all foster care placements is 19.2 percent. The median change between the percent of the neighborhood under 18 had the smallest difference between first foster care placement and all foster care placements with a one percent difference.

## 4.4 Summary

The number of children in the Connecticut foster care system represents one percent of the children in the U.S. foster care system (The Annie E. Casey Foundation, 2021). The children in the Connecticut foster care system experience similar trends as the nationally reported data. The number of children who had one or two foster care placements in the data provided by Connecticut DCF was 60.5 percent, whereas the average number of children with one or two foster care placements in the U.S. is 59 percent (Child Trends, 2020). The racial composition of children in foster care is similar to the national population, with non-Hispanic White children representing 46 percent of the national foster care population and 35 percent of the foster care population in Connecticut, which is proportional to the state's population (The Annie E. Casey

Foundation, 2021; U.S. Department of Commerce, Census Bureau, 2020b). The data provided by Connecticut's DCF provides a holistic picture of the characteristics of children in foster care and the experiences regarding geographic placement challenges while in foster care.

# 5. RESULTS

Chapter 5 shows the results of the research questions and methodology in Chapter 3 and the data in Chapter 4. The first section of this Chapter discusses the variable selection for the Census tracts used in RQ 1 and RQ2. The second section shows the population factors affecting foster care days, number of placements, and distance from home and placements using negative binomial regression, OLS, hot spot analysis, and T-Tests for RQ 1. The third section lists the results of RQ2 and RQ3 foster care outcomes based on a child's FDR using hierarchal models and NYTD survey results using logistic regression. The last section in this chapter is the placement setting results using multinomial regression for RQ 4.

## 5.1 Variable Selection

The population and socioeconomic factors used for this dissertation were reduced through Lasso regression modeling that systematically selects a subset of variables. The negative binomial regressions, OLS, and hierarchal models use socioeconomic and population characteristics to understand the community where children are placed in foster care and where children resided before they entered foster care. The first set of Lasso regression models is based on the child's home Census tract before entering foster care. The second set of Lasso regression models is based on the child's foster care placement Census tract. For both the child's home Census tract and the child's placement Census tract, the regression models look at days in foster care, the number of foster care placements, and the distance to the child's foster care placements based on the child's home or the child's foster care placement. Table 5-1 shows the coefficients from the six Lasso regression models.

**Table 5-1. Lasso Variable Coefficient Selection**

| | Home | | | Placement | | |
|---|---|---|---|---|---|---|
| | Number of Placements | Days in Placement | Average Distance from Home | Number of Placements | Days in Placement | Average Distance from last Placement |
| (Intercept) | 503.94 | 503.94 | 78.81 | 649.77 | 4.27 | 14.11 |
| Median Household Income | . | . | 0 | 0 | . | 0 |
| **Percent Hispanic** | **0.31** | **0.31** | -38.45 | **.** | **.** | -4.00 |
| Percent Non-Hispanic White | . | . | -26.88 | 106.58 | . | -0.52 |
| **Percent Non-Hispanic Black** | **.** | **.** | -43.44 | **210.75** | **0.39** | **-**5.1 |
| **Percent Public Assistance** | **234.69** | **234.69** | -21.68 | **148.97** | **0.76** | -2.8 |
| Percent Households that Rent | . | . | 5.81 | -143.04 | -0.3 | -5.38 |
| **Percent Below Poverty** | **36.13** | **36.13** | -15.4 | **39.58** | **.** | -0.82 |
| Percent High School Education | . | . | -17.69 | 2.57 | -0.23 | -8.38 |
| Percent College Education | . | . | -28.24 | 78.51 | . | -6.58 |
| **Percent Under 18** | **146.09** | **146.1** | **24.58** | **84.91** | -0.52 | **6.47** |
| **Percent Unemployed** | **.** | **.** | **48.87** | -561.37 | -1.87 | **9.18** |
| **Percent Urban** | **1.15** | **1.15** | -13.69 | **91.97** | **.** | -3.34 |
| Percent Female Head of Household | . | . | -0.04 | . | 0.41 | -2.46 |

The negative binomial models, OLS, and the hierarchal models use the same variables to remain consistent across the different types of analysis in this dissertation. The variables were selected if there were two positive coefficients across the six models. Coefficients of zero indicate no relationship with the predictor. Median household income is the only variable with a zero coefficient across the six models. Based on the Lasso results, the Census tract variables chosen include percent Hispanic, non-Hispanic Black, under 18, urban, public assistance, poverty, and unemployment, which are bolded in Table 5-1.

## 5.2 Population Factors

Ecological and population indicators that affect placement stability factors of (1) days in foster care, (2) number of foster care placements, and (3) distance from a child's home to their foster care placements use negative binomial regression and OLS regressions. The negative binomial regressions are used to understand the days in foster care and the number of foster care placements since the dependent variables are counts. The OLS regressions are used to understand the distance from a child's home to their foster care placements since the dependent variables are continuous. The independent variables in the negative binomial and OLS regressions are the population and ecological factors discussed in section 5.1 through Lasso regression.

### 5.2.1 Days in Foster Care

#### *5.2.1.1 Negative Binomial Regression*

A child's time in foster care is an important measure in determining foster care outcomes. The independent variables are the population and socioeconomic Census tracts (i.e., neighborhoods) of the child's home or foster care placement. Four negative binomial regressions are used to determine which independent variables affect a child's time in foster care. These four models focused on different geographic influences a child experiences in foster care (1) the Census tract of the child's home before they entered foster care, (2) the location of the Census tract of each foster care placement, (3) the absolute value change of the Census tract after the first foster care placement, and (4) the absolute value change of all Census tracts foster care placements.

Table 5-2 shows the negative binomial regression results. All four models have a significant log-likelihood score, indicating that each model explains a significant amount of variance in the days spent in foster care. Pearson Chi-square is greater than 0.05 for all the models, and the p-values are less than 0.05 for all models. Many of the explanatory variables are insignificant in the models, except for those related to the placement Census tract. While many of the variables within the models are significant explanatory factors of the number of days a child spent in foster care, each model had one or two significant drivers, which varied across the models.

**Table 5-2. Negative Binomial Models on Days in Foster Care using Neighborhood Characteristics**

| | Home Census Tract | | Placement(s) Census Tract | | Absolute Value Change between Home and 1st Placement | | Absolute Value Change between Home and all Placements | |
|---|---|---|---|---|---|---|---|---|
| n = | 22,456 | | 59,160 | | 22,456 | | 59,160 | |
| Source | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) |
| (Intercept) | 6.22*** | 157.90 | 6.58*** | 345.80 | 6.25*** | 368.00 | 6.51*** | 291.43 |
| % Hispanic | -0.03 | -0.46 | -0.12*** | -3.34 | 0.06 | 1.23 | 0.03 | 1.02 |
| % Non-Hispanic Black | -0.10* | -2.04 | 0.18*** | 6.80 | 0.04 | 1.05 | -0.12*** | -4.23 |
| % Under 18 | 0.22 | 1.50 | 0.27** | 3.22 | 0.16 | 1.01 | 0.28 | 3.36 |
| % Urban | 0.01 | 0.42 | 0.09*** | 6.85 | -0.06** | -3.04 | -0.02 | -1.17 |
| % on Public Assistance | 0.15 | 1.06 | 0.23* | 2.24 | 0.06 | 0.47 | -0.17* | -2.10 |
| % Below Poverty | 0.10 | 1.15 | -0.13* | -2.18 | 0.10 | 1.24 | 0.09 | 1.77 |
| % Unemployed | 0.16 | 0.52 | -1.00*** | -5.19 | 0.42 | 1.54 | 0.38* | 2.22 |
| Log likelihood | -6.343** | | -86.251*** | | -18.385*** | | -30.119*** | |

*** 0.001, **0.01, *0.05

Percent Hispanic and non-Hispanic Black are two variables of Census tracts (i.e., neighborhoods) related to race/ethnicity. Hispanic and non-Hispanic Black Census tracts are significant drivers for the days a child spends in foster care, although the relationship is in the opposite direction for each at the foster care placement Census tract. Non-Hispanic Black Census tracts are not significant in the absolute value change of the Census tract after the first foster care placement. There is a difference between the positive and negative correlation on the percent of the Census tracts that are non-Hispanic

Black for the other three models. For both the home Census tract and the absolute change between home and all foster care placements, there is a negative association, whereas the location of the foster care placements is a positive correlation for days spent in foster care. The results show that race and ethnicity of the placement Census tract and the time spent in foster care are significant and that children who come from Census tracts that have a smaller proportion of non-Hispanic Black population individuals spend less time in foster care. Census tracts where children are placed in locations with a higher level of non-Hispanic Black individuals than their home Census tracts also spend less time in foster care. The absolute value change of the first foster care placement was not a significant driver for the percentage of the Census tract that is non-Hispanic Black or Hispanic.

Census tracts with a greater percentage of the population under 18 are significantly linked to days in foster care at the foster care placement Census tract. The percent of the population under 18 is not significant in days in foster care from the home Census tract or during the placement change modes. The variable related to urbanicity is only significant with the Census tract change of the home and the first foster care placement and the Census tract of all foster care placements. Children who are placed in more urban Census tracts spend more time in foster care. Additionally, the level of urbanicity is not a significant factor related to the child's home Census tract.

The variables related to socioeconomics, including public assistance, poverty, and unemployment, are not significant explainers of days spent in foster care for the models based on the location of the child's home before they entered foster care. Yet, these measures are significant at the location of the foster care placement in days spent in foster care. The change in Census tract socioeconomics after the first foster care placement follows a similar pattern as the child's home.

An additional negative binomial regression analysis (Appendix D) combines all of the home Census tract, placement Census tract, and the absolute value change of the Census tract. The model was run first with all the Census tract environments and then using Lasso regression to reduce multicollinearity within the model. The variables were selected if there were two positive coefficients across the six models (days in care, number of foster care placements, distance from home, and distance from last foster care placement). The model for days in foster care with all Census tracts that the Census tract associated with the foster care placement is still a significant driver for all Census tract placements. For the home Census tract, the only driver that is not a significant influence in the combined Lasso regression model is Census tracts with a higher percent of the population under 18. None of the population or socioeconomic variables are significant drivers based on the Census tract change.

#### *5.2.1.2 Spatial Autocorrelation*

Figure 5-1 shows where children spend the most time in foster care in a choropleth map and a hot spots analysis for the number of days in foster care based on where the child lived before entering foster care and at the location of the foster care placement. The Global Moran's *I* for the location of the child's home hot spot map in

Figure 5-1 is 0.01 with a p-value of 0.58, and for the location of the foster care placement, the Global Moran's *I* is 0.08 and the p-value is 0.0001.

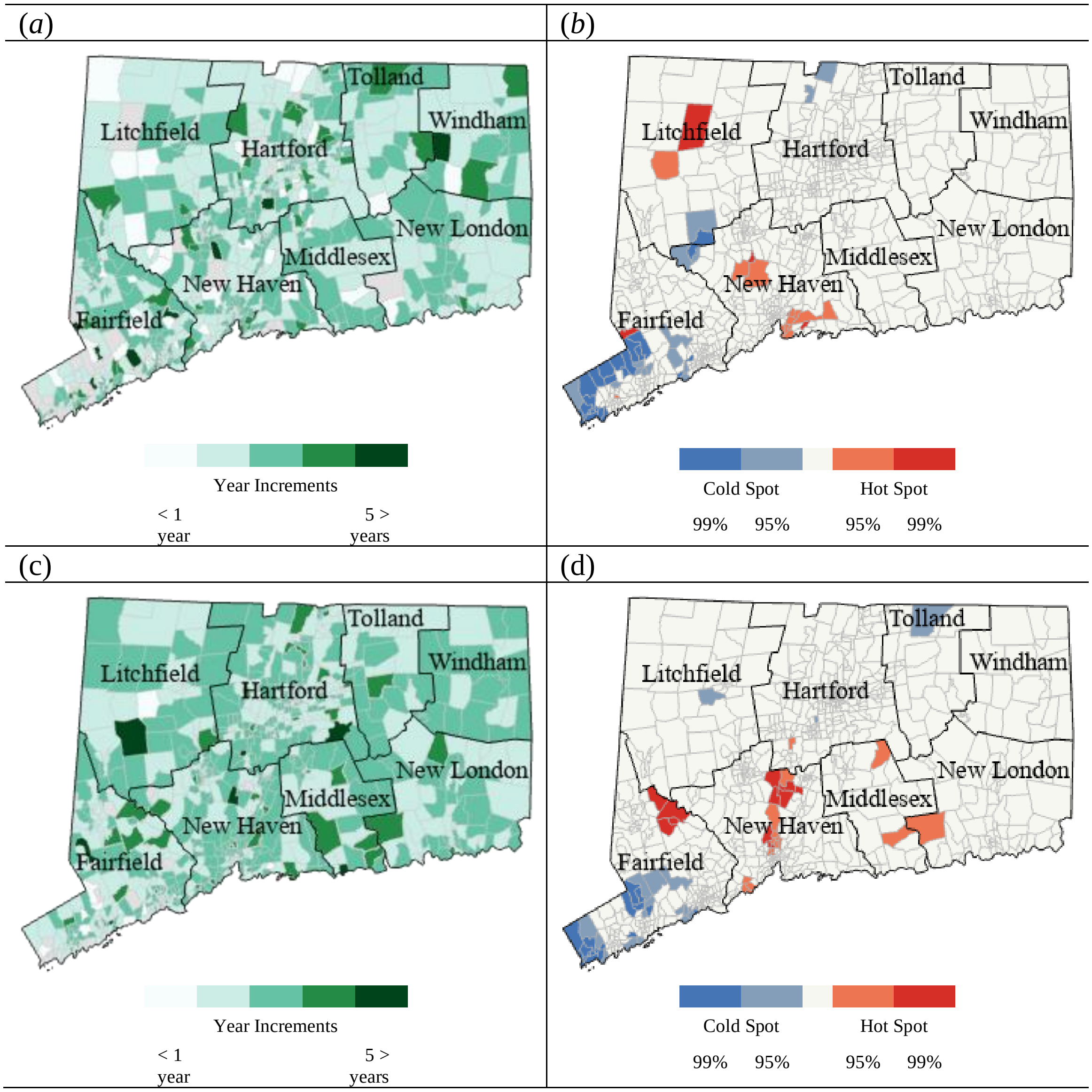


**Figure 5-1. Time in Foster Care**
(*a*) The average time a child spends in foster care based on the location of the child's home
(*b*) Hot spot map of the average time a child spends in foster care based on the location of child's home
(*c*) The average time a child spends in foster care based on the location of the foster care placement
(*d*) Hot spot map of the average time a child spends in foster care based on the location of the foster care placement

Figure 5-1 shows in maps (a) and (b) the location of the child's home before they entered foster care based on the average time a child spends in foster care. Maps (c) and (d) are based on the average time a child spends in their foster care placement. The hot spot maps show that their hot spots in Hartford County where children who entered foster care and spent longer in foster care and had longer foster care placements in New Haven County. Fairfield County has a number of cold spots for both the home Census tract and the foster care placement Census tract.

Table 5-3 shows the results of a t-test that compares the mean of the hot spots and cold spots and determines if the mean is higher or lower in the hot spots and cold spots for children's time spent in foster care. The variables used for the t-test are the same independent variables used in the negative binomial regression for days spent in foster care. If the result of the t-test was insignificant, a dash is designated.

**Table 5-3. Time in Foster Care Hot Spots and Cold Spots T-Test Results**

| | Home Census Tract | | Placement Census Tract | |
|---|---|---|---|---|
| | Cold Spot | Hot Spot | Cold Spot | Hot Spot |
| n | 40 | 18 | 38 | 31 |
| % Hispanic | High*** | - | - | High*** |
| % Non-Hispanic Black | High*** | - | - | - |
| % Under 18 | High*** | - | High** | - |
| % Urban | - | - | - | - |
| % on Public Assistance | High*** | - | High* | Low*** |
| % Below Poverty | High*** | - | - | Low*** |
| % Unemployed | High** | - | - | Low*** |

\- insignificant
*** 0.001, **0.01, *0.05

Table 5-3 shows that the Census tract variable means are lower in the cold spots. The urbanicity of the Census tract is not significant at the home or placement cold or hot spots. The socioeconomic variables at the cold spot Census tracts were higher than the mean; however, the same variables are lower at the placement Census tracts. None of the home Census tract's hot spots are significant.

Identifying the location of hot and cold spots where children spend time in foster care can provide DCF with a number of strategies to help children and families involved with the foster care system. For example, the location of these services could help inform DCF where services are needed to reduce the time a child spends in foster care based on the child's home Census tract and inform what types of foster care placements are needed to reduce the time a child spends in foster care.

#### *5.2.1.3 Summary of Days in Foster Care*

The negative binomial regression found that the child's foster care placement location is a significant driver in the number of days that a child spends in foster care. While many of the variables across the four models are significant explanatory factors of the number of days a child spent in foster care, each model had one or two significant drivers, which varied across the models. The population variables and the socioeconomic variables, poverty, public assistance, and unemployment are not significant factors in the child's home Census tract before they entered foster care. This suggests that efforts to provide preventative services based on the socioeconomic status of the source neighborhoods may not be the most efficient place to locate and focus resources.

The hot spots analysis found that many of the hot spots where children spend time in foster care based on the location of their home or foster care placement are below the mean of the population of the socioeconomic characteristics for the cold spots. There are several hot spots based on where a child lived before, they entered foster care and their foster care placements. Identifying the hot spots and neighborhood drivers where children spend the most time in foster care before they enter foster care and during their time in foster care identifies where prevention and wrap-around services are needed for children and families to reduce a child's time spent in foster care.

### 5.2.2 Number of Placements

#### *5.2.2.1 Negative Binomial*

The number of foster care placements is an essential measure of understanding placement stability for children in foster care. Like the previous section on days in foster care, the number of foster care placements that a child has is examined by the average number of foster care placements of (1) the Census tract from the child's home, (2) the child's foster care placement, (3) the absolute value change between the home, and the first foster care placement, and (4) the absolute value change between home and all foster care placements. The negative binomial regression analysis results are in Table 5-4. Many of the explanatory variables were not significant in the models, except for those related to the placement Census tract and the absolute value change between the home Census tract and all subsequent placement Census tracts.

**Table 5-4. Negative Binomial Regressions Based on Number of Foster Care Placements Based on Neighborhood Characteristics**

| | Home Census Tract | | Placement(s) Census Tract | | Absolute Value Change between Home and 1st Placement | | Absolute Value Change between Home and all Placements | |
|---|---|---|---|---|---|---|---|---|
| n = | 22,456 | | 59,160 | | 22,456 | | 59,160 | |
| Source | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) |
| (Intercept) | 0.93*** | 38.14 | 1.47*** | 114.00 | 0.95*** | 90.53 | 1.42*** | 100.66 |
| % Hispanic | -0.04 | -1.00 | -0.02 | -0.84 | -0.01 | -0.33 | -0.04* | -2.08 |
| % Non-Hispanic Black | 0.04 | -1.28 | 0.14*** | 7.53 | -0.01 | -0.48 | -0.04* | -2.03 |
| % Under 18 | 0.08 | 0.90 | -0.16** | -2.74 | 0.09 | 0.97 | 0.09 | 1.71 |
| % Urban | 0.00 | -0.04 | -0.01 | -0.89 | 0.00 | 0.09 | -0.05*** | -3.60 |
| % on Public Assistance | 0.04 | 0.50 | 0.32*** | 4.71 | -0.02 | -0.28 | 0.01 | 0.26 |
| % Below Poverty | 0.10* | 1.98 | -0.07 | -1.90 | 0.12* | 2.44 | 0.01 | 0.36 |
| % Unemployed | 0.23 | 1.25 | -0.60*** | -4.57 | 0.04 | 0.25 | 0.44*** | 4.12 |
| Log likelihood | -59.13*** | | -59.13*** | | -6.10** | | -24.10*** | |

*** 0.001, **0.01, *0.05

The average number of foster care placements is significant in placement change of all Census tracts and follows a negative direction for non-Hispanic Black and Hispanic Census tracts except for foster care placement Census tracts. This shows that the smaller the non-Hispanic Black and Hispanic population, the fewer number of foster care placements a child is likely to have. Placement Census tracts with a greater population of non-Hispanic Black individuals are associated with a higher number of overall placements. The home Census tract racial composition and the absolute value change of the Census tracts are not significant factors related to the number of foster care placements.

The population under 18 is a significant driver in the number of foster care placements in the foster care placement Census tract. The smaller the population under the age of 18 at the foster care placement, the more likely a child will experience more foster care placements. Whereas the population under 18 is not a significant driver in days in foster care from the home Census tract or during the placement change modes. The variables related to the urbanicity of the Census tract are the only significant drivers with the Census tract change measured by the absolute value of the home and all foster care placements. The percentage that a Census tract that is urban is not a significant driver related to the number of foster care placements a child has at either the home, placement, or first placement change.

The variables related to socioeconomics include public assistance, poverty, and unemployment. Poverty is the only socioeconomic variable that is significant in the home Census tract and the absolute value change of the first foster care placement and all home Census tract. Unemployment is the only significant socioeconomic variable in the absolute value change between the home Census tract and all foster care placement Census tracts. Public assistance and unemployment are significant drivers in Census tract placements; however, in the opposite direction with similar variance. For the home Census tract, public assistance and unemployment are not significantly associated with the number of foster care placements. The results show that socioeconomic influences vary on the effect on the number of foster care placements that a child has before they enter foster care and at their foster care placements.

An additional negative binomial regression analysis is located in Appendix D that combines all of the home Census tract, placement Census tract, and the absolute value change of the Census tract. The model was run first with all the Census tract environments and then using Lasso regression to reduce multicollinearity within the model. The variables were selected if there were two positive coefficients across the six models (days in care, number of foster care placements, distance from home, and distance from last foster care placement). The reduced Lasso regression of the combined models shows that socioeconomic drivers are significantly associated with the number of foster care placements at the placement Census tract. At the home Census tract, poverty is not a significant driver for the number of foster care placements a child has. None of the population or socioeconomic variables are significant drivers based on the Census tract change.

#### *5.2.2.2 Spatial Autocorrelation*

The maps in this section show (1) where children had the most foster care placements based on the location of the child's home before they entered foster care and the location of the foster care placement, and (2) the location of hot spots and cold spots where children had the most foster care placements based on the location of the child's home before they entered foster care and the location of the foster care placement.

Figure 5-2 shows the average number of foster care placements that children had based on the location of their home before they entered foster care and at their foster care placement and hot spots where children had the most foster care placements. The Moran's *I* for the average number of placements based on the home Census tract Figure 5-2 is 0.01 and has a p-value of 0.004, and for the average number of placements at the placement, Census tract is 0.1 and has a p-value of 0.0001.

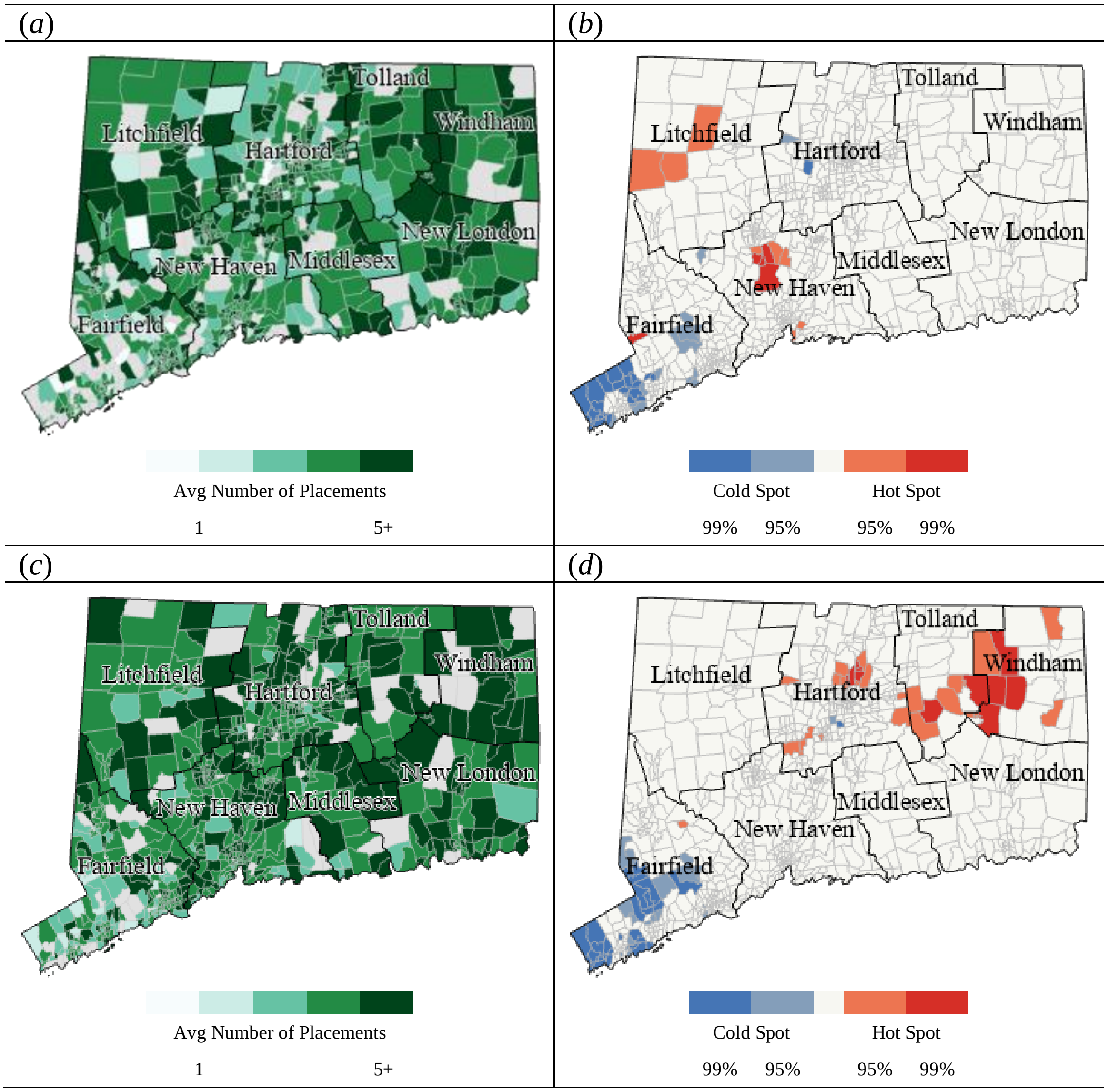


**Figure 5-2. Average Number of Foster Care Placement**
(*a*) The average number of foster care placements a child has in foster care based on the location of the child's home
(*b*) Hot spot map of the average number of placements a child has in foster care based on the location of the child's home
(*c*) The average number of foster care placements a child has based on the location of the foster care placement
(*d*) Hot spot map of the average number of placements a child has based on the location of the foster care placement

The maps in Figure 5-2 show a few hot spots in New Haven and Litchfield Counties based on the location of the child's home Census tract. However, the hot spots based on the number of foster care placements based on the child's placement Census tract are in Tolland and Windham County. The majority of the cold spots at both the location of the child's home and foster care placements for the number of foster care placements are located in Fairfield County.

Table 5-5 shows the results of a t-test that compares the mean of the hot spots and cold spots and determines if the mean is higher or lower in the hot spots and cold spots based on the number of foster care placements. The variables used for the t-test are the same independent variables used in the negative binomial regression for the number of foster care placements. If the result of the t-test was insignificant, a dash is designated.

**Table 5-5. T-Test Hot Spot Results on Number of Foster Care Placements**

| | Home Census Tract | | Placement Census Tract | |
|---|---|---|---|---|
| | Cold Spot | Hot Spot | Cold Spot | Hot Spot |
| n | 39 | 13 | 49 | 38 |
| % Hispanic | High** | - | Less*** | Low* |
| % Non-Hispanic Black | High*** | High* | Less*** | Low* |
| % Under 18 | Low*** | - | High*** | Low* |
| % Urban | - | - | - | - |
| % on Public Assistance | Low*** | High* | Low*** | - |
| % Below Poverty | Low*** | - | Low*** | - |
| % Unemployed | Low*** | - | - | High*** |

- insignificant
*** 0.001, **0.01, *0.05

Table 5-5 shows that the mean Census tract variables are significantly higher than the population for public assistance at the home Census tract hot spots and higher for unemployment at the hot spots for placement Census tracts. The socioeconomic variables that are significant are lower in the cold spots for a number of foster care placements based on the child's home or location of the foster care placements. The percent of the population that is Hispanic is lower at the placement cold spots, whereas it is higher at the home Census tract cold spots. Urbanicity is not significant for either the hot or the cold spot maps for the number of foster care placements based on the child's home or location of the foster care placement.

#### *5.2.2.3 Summary*

The negative binomial regression found that the child's foster care placement location is a significant driver of the number of foster care placements. While many of the variables across the four models are significant explanatory factors of the number of foster care placements, each model had one or two significant drivers, which varied across the models. The socioeconomic Census tract variables related to poverty, public assistance, and unemployment varied in significance across the models. Poverty is the only significant driver in the home Census tract in relation to the number of foster care placements, with increases in poverty at the home Census tract contributing to more foster care placements. Higher poverty levels at the home Census tract related to multiple foster care placements is a significant finding since poverty is a significant driver in relation to child maltreatment cases before a child enters foster care (Coulton et al., 2007). The level of urbanicity of the Census tracts was not a significant driver related to the number of foster care placements at the home Census tract, the placement Census tract, and the absolute value change of the Census of the first foster care placement. The results of these models show that if resources are provided based on a Census tract (i.e., community's) needs, it could influence the number of foster care placements that a child has. For example, Census tracts with more foster care placements also have an increase in public assistance. By providing more public assistance to these Census tracts, it may reduce the need for a child to change foster care placements.

### 5.2.3 Distance

#### *5.2.3.1 OLS*

The models related to distance use OLS regression instead of negative binomial regression since the data is not based on counts like the other models in this section. Distance is calculated in two ways, (1) the average distance from home and (2) the average distance from the last foster care placement. The dependent variables are the same dependent variables used in the negative binomial regressions to understand the days spent in foster care and the number of foster care placements. Table 5-6 shows the results of the OLS regression models with (1) the average distance from home based on the home and placement Census tract, (2) the average distance from placement based on the home and placement Census tract, and (3) the absolute value change of the first foster care placement, and (4) the absolute value between home and all foster care placements. White's test is used to correct for heteroscedasticity for all of the results in Table 5-6.

**Table 5-6. OLS Regression Average Distance Change by Census Tract**

| | Average Distance from Home | | | | Average Distance from Placement | | | | Distance from Home to Foster Care Placement | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Home Census Tract | | Placement(s) Census Tract | | Home Census Tract | | Placement(s) Census Tract | | Absolute Value Change between Home and 1st Placement | | Absolute Value Change between Home and all Placements | |
| n = | 22,456 | | 59,160 | | 22,456 | | 59,160 | | 22,456 | | 59,160 | |
| Source | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) |
| (Intercept) | 35.50*** | 0.00 | 26.37*** | 2.18 | 30.92*** | 2.28 | 21.19*** | 1.87 | 28.44*** | 0.39 | 27.29*** | 0.25 |
| % Hispanic | 5.82 | 5.49 | 2.78 | 4.46 | 6.09 | 3.78 | 6.52 | 3.98 | 1.98 | 1.15 | -0.06 | 0.72 |
| % Non-Hispanic Black | -10.77** | 3.50 | -5.70 | 2.91 | -9.76*** | 2.34 | -9.15*** | 1.87 | -4.99*** | 0.87 | -3.93*** | 0.58 |
| % Under 18 | 0.63 | 10.71 | -9.84 | 8.21 | 24.63* | 9.67 | 9.22 | 7.99 | -9.33** | 3.35 | -7.88*** | 2.18 |
| % Urban | -7.75*** | 1.83 | -5.32*** | 1.42 | -6.93*** | 1.65 | -3.33** | 1.24 | 17.44*** | 0.51 | 11.41*** | 0.33 |
| % on Public Assistance | -26.10 | 13.62 | -22.06* | 9.85 | -33.53* | 13.15 | -29.71** | 9.65 | -1.79 | 2.99 | -3.49 | 1.94 |
| % Below Poverty | -4.80 | 8.38 | -1.03 | 7.62 | -18.49* | 7.58 | 1.62 | 5.94 | -9.74*** | 1.73 | -6.79*** | 1.11 |
| % Unemployed | 38.61 | 25.48 | 42.26* | 20.30 | 29.07 | 21.25 | 10.34 | 16.54 | -0.60 | 6.03 | -1.65 | 3.89 |
| F-Statistics | 10.11*** | | 6.57*** | | 21.58*** | | 14.12*** | | 185.1*** | | 200.7*** | |
| $R^2$ | 0.06 | | 0.05 | | 0.13 | | 0.06 | | 0.08 | | 0.14 | |

*** 0.001, **0.01, *0.05

The percent of the Census tract that is Hispanic is not a significant driver in the six OLS models that examine various types of distance. Census tracts that are non-Hispanic Black are a significant driver for many of the models. The distance a child is placed from the home Census tract for both the average distance from home and the average distance placement from home has the greatest significance for Census tracts whose non-Hispanic Black population is smaller. For the other models, the distance calculation for the non-Hispanic Black Census tract is significant and has a negative coefficient. This shows that distance to foster care placement and from home increases for Census tracts with a smaller population that is non-Hispanic Black. The percentage that a Census tract is non-Hispanic Black is not significantly associated with the average distance from home based on the location of the placement Census tract.

Census tracts with a younger population are significantly associated with the child's home Census tract using the average distance from placement change and absolute calculation of the change of both the first foster care placement and all foster care placements. The percent of Census tracts with a population under 18 is not significantly related to the placement Census tracts with either the average distance from home or the average distance from placement, and the home Census tract is based on the average distance from home. The Census tract variable percent urban is consistent across all the models and has a negative coefficient for both the average distance based on the home and placement Census tract. However, there is a positive correlation with the level of urbanicity for the absolute value change. This shows that children whose home Census tract or placements Census tract is more urban, the further they will be placed.

The socioeconomic variables in Table 5-6 also do not show a consistent relationship in the six models. Public assistance has a negative coefficient across all the models. The only model with a positive coefficient related to poverty is the average distance from home at the placement Census tract, which shows that children in areas of higher poverty experience greater distance in foster care placements. Unemployment has the largest coefficients when calculating the average distance from home or the average distance from the last foster care placement. The average distance from home is only significant in the models that use the average distance from home based on the home or placement Census tract. Poverty is not a significant driver for the average distance from home, and the home or placement Census tract nor is it significant at the placement Census tract for the average distance from placement. The level of unemployment is also not a significant factor in the home Census tract for the average distance from home, the home and placement Census tract for the average distance from placement of the absolute value change of the home, or the placement Census tract.

An OLS analysis is located in Appendix E that combines all of the home Census tract, placement Census tract, and the absolute value change of the Census tract. The model was run first with all the Census tract environments and then using Lasso regression to reduce multicollinearity within the model that looks at the distance to foster care placements from the home Census tract and the placement Census tract. The variables were selected if there were two positive coefficients across the six models (days in care, number of foster care placements, distance from home, and distance from last foster care placement). The socioeconomic and population factors are all significant drivers in the Lasso combined regression except for the population under 18 at the placement Census tract. The reduced Lasso regression for distance from the last foster care placement shows that all of the socioeconomic and population factors for the placement Census tract are significant drivers except for Census tracts where there is a larger population under 18. Poverty is not a significant driver for distance from the last foster care placement at the home Census tract, where the population that has less public assistance is a significant driver from the last foster care placement. The only socioeconomic driver that is not significant in Census tract change for distance from the last foster care placement is the percent of the population on public assistance.

#### *5.2.3.2 Spatial Autocorrelation*

Figure 5-3 shows the hot spots of the average distance from home based on where the child lived before entering foster care and the average distance from the foster care placement. Ideally, a child will be placed closer to home to maintain a stable environment (American Bar Association Center on Children and the Law, Education Law Center and Juvenile Law Center, 2011). The Moran's *I* for the average distance based on the home Census tract in map *b* is 0.39 and has a p-value of 0.0001, and the distance from the placement map *d* has a Moran's *I* of 0.21 and has a p-value of 0.0001.

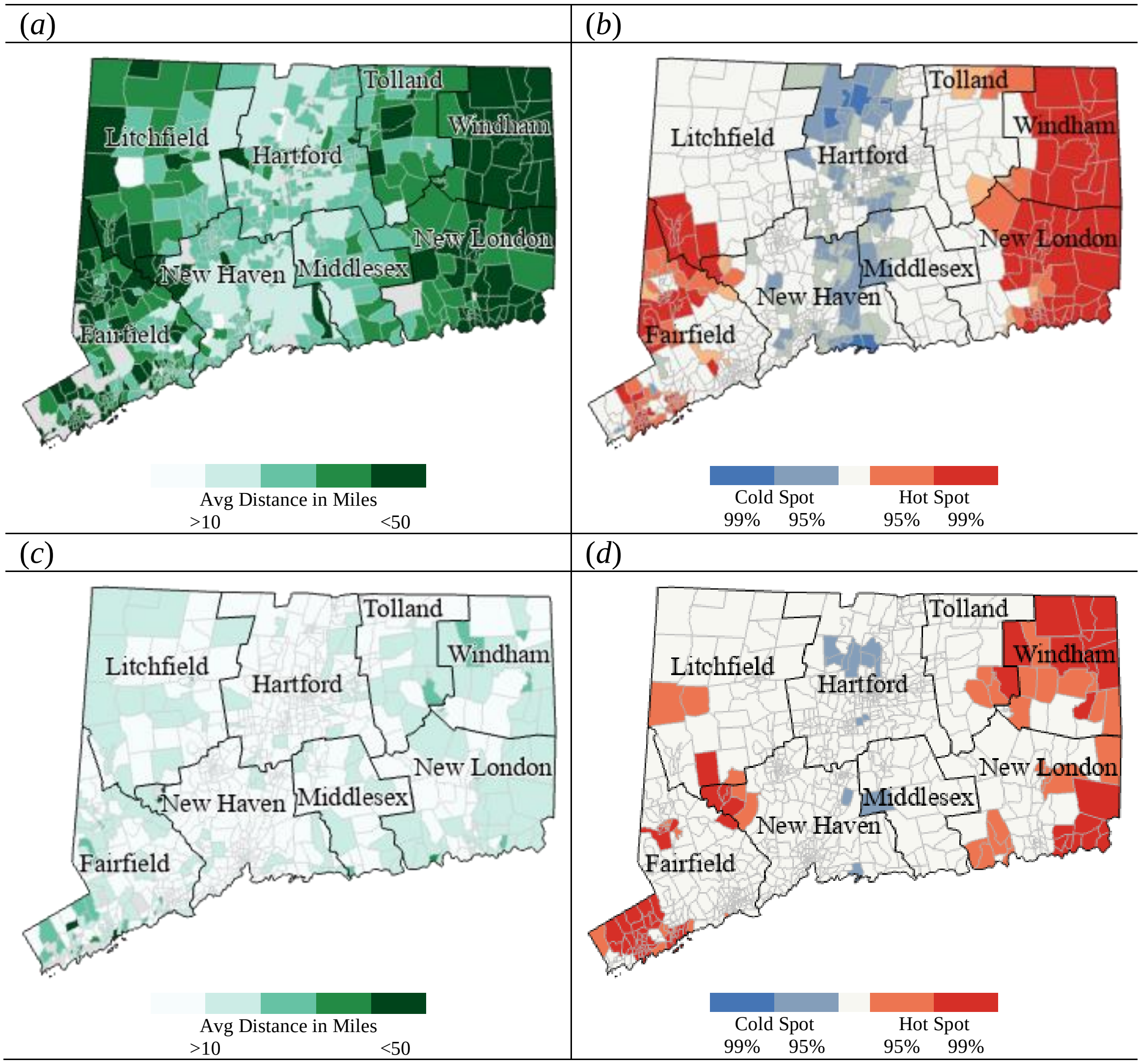


**Figure 5-3. Average Distance**

(*a*) The average distance from home based on the location of the child's home
(*b*) Hot spot map of the average distance from home based on the location of the child's home
(*c*) The average distance from placement based on the location of the foster care placement
(*d*) Hot spot map of the average distance from placement a child has based on the location of the foster care placement

The maps in Figure 5-5 show similar patterns of hot spots and cold spots related to distance from home and distance from foster care placement. The hot spots in Figure 5-5 follow the same patterns of hot spots and cold spots, with most of the hot spots located on the borders of the state and the cold spots located in the center of the state. The hot spots in these maps could result in the border between Connecticut and Rhode Island and children needing to be placed further from home or lack of foster care placements.

Table 5-7 shows the results of a t-test that compares the mean of the hot spots and cold spots and determines if the mean of the Census tract variable is higher or lower in the hot spots and cold spots for children based on the distance to foster care placements based on either the home of the child or the last foster care placement. The variables used for the t-test are the same independent variables used in the OLS regression for the distance to foster care placements. If the result of the t-test was insignificant, there is a dash in the table.

**Table 5-7. T-Test Hot Spot Results on distance from home and placement**

| | Home Census Tract | | Placement Census Tract | |
|---|---|---|---|---|
| | Cold Spot | Hot Spot | Cold Spot | Hot Spot |
| n | 75 | 158 | 12 | 120 |
| % Hispanic | - | - | - | - |
| % Non-Hispanic Black | - | High* | High** | Less** |
| % Under 18 | - | - | - | - |
| % Urban | - | Less*** | - | Less*** |
| % on Public Assistance | - | High*** | - | Less*** |
| % Below Poverty | - | High*** | - | - |
| % Unemployed | - | - | - | - |

- insignificant
*** 0.001, **0.01, *0.05

The results of the t-test show that most of the cold spots Census variables were insignificant except for Census tracts at the foster care placement where the population is higher than the mean for the non-Hispanic Black population. The mean of the hot spots based on the home Census tract for distance from home is higher than the mean population for the percent of the population that is non-Hispanic Black, below poverty and unemployment. Whereas the mean is lower for the level of urbanicity of the home Census tract based on the distance from home. At the placement Census tract, the distance from placement hot spots, the mean of the population was lower for the non-Hispanic Black population, urbanicity, and poverty.

#### *5.2.3.3 Summary*

Distance is a complex measure that needs to be considered from multiple angles. The distance that a child is placed from their home is measured in multiple ways in this section. While many of the variables across the six OLS models are significant explanatory factors, the distance a child was placed from their home and their last foster care placement had several significant drivers. However, the significance of the drivers varied across the models. The distance models that look at the change of the neighborhood type between the first foster care placement and all foster care placements had the most drivers that were significant. These considerations on neighborhood change should be examined when placing children in foster care. Policies should be created to help children acclimate to their new Census tract (i.e., neighborhood) when the population and socioeconomic changes of the neighborhood are significantly different from where the Census tract that a child used to live.

### 5.2.4 Population Factors Summary

The negative binomial and OLS regression analysis in this section used the same population and socioeconomic variables to understand (1) the days a child spends in foster care, (2) the number of foster care placements, and (3) the distance from a child's home. The various models showed that the location of the foster care placement had the most apparent drivers related to days spent in foster care, number of foster care placements, and distance from home and foster care placements.

Across the negative binomial and OLS models, race/ethnicity is relatively consistent in significance and direction when examining the days a child spends in foster care, the number of foster care placements, and the distances from home. Census tracts that have a smaller population of Non-Hispanic Black population typically have children with fewer days in foster care, number of placements, and placements with smaller distances to foster care placements.

Population under 18 of the Census tracts had similar results in the days in foster care models and the number of foster care placement models, with it being significant, albeit in opposite directions at the foster care placement Census tract. The urbanicity of the Census tract was significant in all of the distance models. However, urbanicity was only a significant driver during the days in foster care at the placement Census tract and placement change of the first Census tract. In contrast, urbanicity was only significant at the change of all foster care placements.

The socioeconomic variables showed the biggest shift between all the Census tract variables identified through Lasso regression across the models addressed in the section. The socioeconomic variables in the distance models showed the biggest variance compared to the models that looked at the days in foster care and the number of foster care placements. In general, the socioeconomic variables were more significant in the models based on the placement Census tract instead of the home Census tract. The findings in this section are supported by the socioeconomic and population characteristics used in the child maltreatment literature to identify neighborhood predictors (Coulton et al., 2007).

## 5.3 Foster Care Outcomes

Two sets of variables are used to assess drivers of a child's outcomes after leaving foster care. The first set of dependent variables are the federal discharge reason (FDR) from foster care, with a specific look at whether the child achieved permanency or did not achieve permanency. The second set of variables used to determine foster care outcomes are the NYTD survey outcomes. The independent variables are related to the child, including age at foster care entry, race, number of foster care placements, time in foster care, and distance from foster care placement. The neighborhood factors in the hierarchal models were determined from the LASSO results, as shown in the previous section.

The dependent variables are dichotomous (yes/no) variables indicating if the child achieved permanency based on a child's positive or negative FDR. The FDR of the child's last foster care episode is used to determine if a child achieved permanency. For this dissertation, a child achieves permanency if they are reunited with their parents, obtain guardianship, are adopted, or are placed with other relatives. Children who did not achieve permanency exited foster care through emancipation, transfer to another agency, death, missing, or because they were a runaway. The second set of dependent variables are based on the survey responses of youth who participated in the NYTD survey focusing on the survey questions related to incarceration, high-risk behaviors, and homelessness. The comparison dependent variable for race/ethnicity for the child is non-Hispanic Black for this results section.

### 5.3.1 Federal Discharge Reason

Hierarchical regression is used to determine which of the child's characteristics and neighborhood characteristics affect a child's FDR. Table 5-8 and Table 5-9 are the results from two hierarchal models that examine FDR by (1) examining the foster care outcome based on the location of 22,456 homes of children before they entered foster care and (2) the child's foster care outcomes based on the location of the 59,160 children's foster care placements.

**Table 5-8. Random Intercept Model Predicting Federal Discharge Reason Based on the Location of the Child's Home Before They Entered Foster Care**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | *B* | *SE* | *B* | *SE* | *B* | *SE* |
| Intercept | 1.51*** | 0.02 | 4.93*** | 0.09 | 4.88*** | 0.14** |
| Level 1 | | | | | | |
| Race | | | | | | |
| Non-Hispanic White | | | 0.26*** | 0.05 | 0.26*** | 0.05 |
| Hispanic | | | 0.14** | 0.05 | 0.14** | 0.05 |
| Non-Hispanic Other | | | 0.28** | 0.09 | 0.28** | 0.09 |
| Age at Entry | | | -5.78*** | 0.10 | -1.47 | 0.23 |
| Total Days in Foster Care | | | -6.46*** | 0.22 | -5.78*** | 0.10 |
| Number of Foster Care Placements | | | -1.47*** | 0.23 | -6.45*** | 0.22 |
| Distance From last Placement | | | 0.00 | 0.00 | 0.00 | 0.00 |
| Level 2 | | | | | | |
| % Hispanic | | | | | 0.16 | 0.16 |
| % Non-Hispanic Black | | | | | 0.15 | 0.14 |
| % Under 18 | | | | | 0.26 | 0.40 |
| % Urban | | | | | 0.03 | 0.10 |
| % on Public Assistance | | | | | -0.33 | 0.40 |
| % Below Poverty | | | | | -0.27 | 0.24 |
| % Unemployed | | | | | -0.38 | 0.82 |

Model 1 = Unconditional Model, Model 2 = Random Intercept, Level-1 Predictors, Model 3 = Random Intercept, Level-1, and Level-2 Predictors.
*** 0.001, **0.01, *0.05

**Table 5-9. Random Intercept Model Predicting Federal Discharge Reason Based on the Foster Care Placement**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | *B* | *SE* | *B* | *SE* | *B* | *SE* |
| Intercept | 1.71*** | 0.03 | 6.33*** | 0.07 | 6.18*** | 0.12 |
| Level 1 | | | | | | |
| Race | | | | | | |
| Non-Hispanic White | | | 0.22*** | 0.03 | 0.21** | 0.03 |
| Hispanic | | | 0.05 | 0.03 | 0.04 | 0.03 |
| Non-Hispanic other | | | 0.31*** | 0.06 | 0.31*** | 0.06 |
| Age at Entry | | | -7.30*** | 0.08 | -1.59*** | 0.10 |
| Total Days in Foster Care | | | -7.80*** | 0.13 | -7.30*** | 0.08 |
| Number of Foster Care Placements | | | -1.59*** | 0.10 | -7.79*** | 0.13 |
| Distance From last Placement | | | 0.03 | 0.08 | 0.02 | 0.08 |
| Level 2 | | | | | | |
| % Hispanic | | | | | 0.12 | 0.18 |
| % Non-Hispanic Black | | | | | -0.38 | 0.14 |
| % Under 18 | | | | | 0.76** | 0.42 |
| % Urban | | | | | -0.16* | 0.07 |
| % on Public Assistance | | | | | 0.54 | 0.50 |
| % Below Poverty | | | | | 0.09 | 0.29 |
| % Unemployed | | | | | 1.88* | 0.96 |

Model 1 = Unconditional Model, Model 2 = Random Intercept, Level-1 Predictors, Model 3 = Random Intercept, Level-1, and Level-2 Predictors.
*p < .10, **p < .05, ***p < .01

The results of the hierarchal model shown in Table 5-8 and Table 5-9 are based on the child's home, and the child's foster care placement showing that race is a significant driver of a child's foster care outcomes. The reference group for the child's race in foster care is non-Hispanic Black as it is the modal value. Children who are not non-Hispanic Black are associated with positive foster care outcomes when they exit foster care based on the location of their home before they entered foster care. The child's race is also significant for children who are not Hispanic based on the location of the child’s foster care placement and not a significant driver for children who are Hispanic for the model that examines the location of the foster care placement. The age when a child enters foster care is a significant driver for the location of the child’s home and foster care placement, with younger children associated with positive foster care outcomes.

Days in foster care and the number of foster care placements are significant drivers related to the location of the child’s home before they enter foster care and the location of the foster care placement. Children who have fewer foster care placements and spend less time in foster care are linked to positive foster care outcomes, which is supported in the literature. Distance, however, is not a significant driver related to a child’s foster care outcomes based on the location of the child’s home or foster care placement.

The socioeconomic and population factors based on the child’s home and foster care placement Census tract (i.e., neighborhood) did not follow similar patterns as did the child’s foster care characteristics between the two models. None of the socioeconomic and population factors for a child’s home before entering foster care are significant. Only three of the socioeconomic and population variables of children’s foster care placements are significant. Census tracts that have a smaller population of the non-Hispanic Black population are associated with positive foster care outcomes, as well as Census tracts that are less urban. Neighborhoods where children in foster care are placed where unemployment is higher, are also linked to children with positive foster care outcomes.

### 5.3.2 NYTD Outcomes

NYTD outcomes are based on a smaller population than the rest of this dissertation since the survey is first administered to youth who are 17 years old while in foster care. The NYTD survey is a common benchmark within the field of Social Work regarding youth outcomes for youth who are in foster care at the age of 17. The NYTD data are based on (1) federally regulated survey questions and (2) federally regulated survey opportunities. At the time of this dissertation's analysis, only one cohort of NYTD data was available. The resulting dataset is the 339 youth who were 17 when the cohort one dataset was administered, which is 1.5 percent of the children and youth in the dataset provided by the Connecticut DCF. Due to the small number of youths who were eligible to participate in the survey, Logistic regression is used to determine how distance affects foster care outcomes for older youth aging out of foster care. The dependent variables focus on three NYTD areas of interest (1) youth who experienced incarceration, (2) youth who experienced homelessness, and (3) youth who participated in high-risk behaviors. Table 5-10 shows the logistic regression results.

**Table 5-10. NYTD Logit Results**

| | Incarceration | | High-Risk Behavior | | Homelessness | |
|---|---|---|---|---|---|---|
| n = 339 | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) |
| (Intercept) | -3.62** | 1.13 | -3.92*** | 1.10 | -4.64*** | 1.59 |
| Non-Hispanic White | -0.67 | 0.35 | 0.09 | 0.33 | -0.26 | 0.46 |
| Hispanic | -0.21 | 0.66 | -0.85 | 0.72 | -0.77 | 1.09 |
| Non-Hispanic Other | -0.14 | 0.35 | -0.13 | 0.35 | 0.37 | 0.44 |
| Age at Removal | 0.17* | 0.07 | 0.21** | 0.06 | 0.17 | 0.10 |
| Total Days in Foster Care | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Number of Foster Care Placements | 0.14* | 0.07 | 0.02 | 0.06 | 0.11 | 0.11 |
| Average Distance from Home | -0.03** | 0.01 | -0.04*** | 0.01 | 0.01 | 0.01 |
| Average Distance from Placement | 0.04* | 0.02 | 0.06*** | 0.02 | -0.02 | 0.02 |
| AIC | | 337.3 | | 361.82 | | 239.53 |

*** 0.001, **0.01, *0.05

The reference group for the child's race in foster care is non-Hispanic Black as it is the modal value. The models that examine youth who were incarcerated, or experienced high-risk behavior had similar drivers, whereas none of the drivers were significant in the homelessness logistic regression model. One noticeable difference between the population characteristics of youth who were incarcerated, or experienced high-risk behavior is that non-Hispanic White youth are more likely to experience risky behavior and less likely to be incarcerated. Youth who are non-Hispanic Other are not significantly associated with high-risk behavior, homelessness, or incarceration compared to non-Hispanic Black children. The logistic regression results show that older children who are still in foster care at age 17 are more likely to be incarcerated or partake in high-risk behavior when they enter foster care.

When looking at a child's experience in foster care, the number of foster care placements is a significant factor for children who have experienced incarceration, with only a slight increase in the number of foster care placements related to a child being incarcerated. The time a child spends in foster care and the number of foster care placements have little effect on the child's outcomes related to high-risk behavior. The distance a child is placed from home is significant for children who experience incarceration and high-risk behavior, and the closer a child is placed to their home, the more likely they are to experience incarceration or participate in high-risk behavior.

### 5.3.3 Foster Care Outcomes Summary

FDR and NYTD survey results are the two outcomes used to understand children in the foster care system. The level one independent variables in the hierarchal models and the independent variables in the logistic regression focus on the child's characteristics and experience in foster care. The age at which a child enters foster care is a significant driver of a child's outcomes. Regardless of the population or socioeconomic conditions of a child's home or placement Census tract, the younger a child is, the more likely they are to experience positive foster care outcomes, including adoption, guardianship, reunification with their family, or living with relatives. When older children enter foster care, the results show they are associated with being incarcerated or participating in high-risk behaviors, which supports previous research (Wulczyn et al., 2002). The child's race is not a driving factor for the youth in the NYTD survey; however, it is a significant driver for children's outcomes related to their FDR.

A child's foster care experience, which includes the days spent in foster care, and the total number of foster care placements, findings are supported by previous research (Koh et al., 2014; Pecora et al., 2006). The days spent in foster care and the number of foster care placements are significant drivers to foster children's outcomes related to a child's FDR. The distance that a child is placed from their home is not a factor that is considered in models looking at a child's foster care outcomes. The distance between foster care placement and the distance from a child's home is not found to be a significant driver related to a child's FDR; however, distance is significant in youth's outcomes reported in the NYTD survey. In the youth reported NYTD result, distance to a child's home or last placement is associated with the child's behavior. The logistic regression results found that when a child is placed closer to their home, they are more likely to be incarcerated or participate in high-risk behaviors. The logistic regression is based on a small sub-population of 337 youth who participated in Cohort 1, year 1, the NYTD survey, which shows that the significance of a child's proximity to their home could adversely affect the child.

## 5.4 Type of Foster Care Placement Setting

When the dependent variable is categorical, MLR is used to examine the likelihood of a particular categorical outcome occurring; in this case, the type of foster care placement is a categorical variable. This section shows the results of two MLR models. The first MLR examines the first foster care placement type; the second model examines all of the child's foster care placements. The categorical dependent variables used in this analysis are the foster family placement types, which include (1) foster family home relative, (2) foster family home non-relative, (3) group home, (4) institution, (5) supervised independent living, and (6) trial home visit. Foster care placements that are trial home visits are excluded from the first MLR model that examines the first placement type. Less than one percent of the first foster care placements are supervised independent living placements. It is rare for a child to be in foster care and have their first foster care placement as a supervised independent living placement. The reference group in both sets of analyses is foster family home non-relative. The independent variables are based on the child's characteristics and their foster care experience, including age they entered foster care, race/ethnicity, number of foster care placements, days in foster care, and distance from home. The reference group for the child's race in foster care is non-Hispanic Black as it is the modal value.

### 5.4.1 First Type of Foster Care Placement

Table 5-11 shows the MLR results for the first foster care placement. The results show that several variables are significantly related to the type of foster care placement a child is first placed in when they enter foster care. Notably, all the variables are significant drivers for a relative foster family home and institutions to how children are placed in foster care. The reference group for the results in Table 5-11 is foster family home non-relative placement types.

**Table 5-11. Multinomial Regression Results for the type of First Foster Care Placement Type**

| | Foster Family Home Relative | | Group Home | | Institution | | Supervised Independent Living | |
|---|---|---|---|---|---|---|---|---|
| n = 22,253 | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) |
| (Intercept) | -0.87*** | 0.05 | -6.94*** | 0.20 | -4.52*** | 0.10 | -14.59*** | 1.16 |
| Age at Removal | 0.40*** | 0.07 | 8.28*** | 0.24 | 6.47*** | 0.12 | 16.11*** | 1.43 |
| Non-Hispanic White | 0.24*** | 0.04 | 0.16 | 0.08 | 0.23*** | 0.06 | -0.42*** | 0.25 |
| Non-Hispanic Other | -0.09*** | 0.05 | -0.02 | 0.09 | -0.12*** | 0.06 | -0.74*** | 0.29 |
| Hispanic | -0.14*** | 0.08 | 0.08 | 0.15 | 0.20*** | 0.10 | -1.36*** | 0.73 |
| Total Days in Foster Care | 3.62*** | 0.20 | 0.74 | 0.48 | 0.60*** | 0.30 | 11.73*** | 1.10 |
| Number of Foster Care Placements | -9.66*** | 0.33 | -0.78*** | 0.44 | -1.53*** | 0.30 | -37.69*** | 4.99 |
| Distance From Home to 1st Foster Care Placement | -0.18*** | 0.09 | 0.17 | 0.18 | -0.37*** | 0.13 | -0.35 | 0.61 |
| AIC 127695.1 | | | | | | | | |
| Log-Likelihood -20043*** | | | | | | | | |

*** 0.001, **0.01, *0.05

The distance for both family homes and institutions foster care placements has a negative coefficient, which shows that the distance decreases for these placements compared to relatives in foster family homes foster care placements. Group homes and institutions are more established community types of foster care placements which is a notable difference in that distance is a significant driver for institutions and not group homes. The only variable that is not significant in supervised independent living placements is the average distance from the last foster care placement. Supervised independent living is often a flexible living arrangement that is often a non-licensed foster care placement which is typically for older children who are aging out of foster care. Average distance to home is not significantly associated with how children are placed in foster care related to supervised independent living placements.

The variables that are not significant to group homes include the child's race and the total time in foster care. These variables may not be significant in group homes due to the nature of the child's needs in foster care and the services provided by group homes. Connecticut has two types of group home classifications (1) therapeutic group homes and (2) Supported Work Education and Training (SWET), which DCF licenses (Connecticut State Department of Children and Families, 2021).

### 5.4.2 Type of Foster Care Placement for every Foster Care Placement

The MLR results in Table 5-12 show that several variables are drivers for how children are placed in foster care compared to foster family homes with non-relatives. Many of the variables are significant in the MLR that looks at every child's foster care placement.

**Table 5-12. Multinomial Regression Results for the type of All Foster Care Placement Types**

| | Foster Family Home Relative | | Group Home | | Institution | | Supervised independent living | | Trial home visit | |
|---|---|---|---|---|---|---|---|---|---|---|
| n=59,160 | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) | Coef. | (SE) |
| (Intercept) | -0.44*** | 0.03 | -6.72*** | 0.12 | -4.86*** | 0.08 | -17.67*** | 0.63 | 0.10* | 0.05 |
| Age at removal | 0.13*** | 0.04 | 8.02*** | 0.14 | 6.87*** | 0.09 | 19.18*** | 0.75 | 1.41*** | 0.06 |
| Non-Hispanic White | 0.04 | 0.03 | -0.11* | 0.00 | 0.08* | 0.04 | -0.48*** | 0.14 | -0.05 | 0.04 |
| Non-Hispanic Other | -0.14*** | 0.03 | -0.12** | 0.05 | -0.15*** | 0.04 | -0.60** | 0.15 | -0.04 | 0.04 |
| Hispanic | -0.13*** | 0.05 | -0.09 | 0.09 | 0.11 | 0.07 | -0.33 | 0.26 | -0.13* | 0.07 |
| Total Days in Foster Care | 0.63*** | 0.11 | 2.13*** | 0.20 | -0.19 | 0.18 | 13.58*** | 0.56 | -6.20*** | 0.27 |
| Number of Foster Care Placements | -5.47*** | 0.15 | -0.42 | 0.17 | -0.71*** | 0.15 | -5.52*** | 0.63 | -9.02 | 0.24 |
| Average Distance from Home | 0.00*** | 0.00 | -0.01*** | 0.00 | -0.01*** | 0.00 | -0.02*** | 0.00 | -0.11*** | 0.00 |
| Average Distance from Placement | 0.00*** | 0.00 | 0.01*** | 0.00 | 0.00*** | 0.00 | 0.01*** | 0.00 | 0.04*** | 0.00 |
| AIC: 122077 | | | | | | | | | | |
| Log-Likelihood -617173*** | | | | | | | | | | |

*** 0.001, **0.01, *0.05

Nearly all the drivers are significant for a relative foster family home, group home, institutions, supervised independent living, and trial home visits to how children are placed in foster care, compared to foster family homes non-relatives. The variable for Hispanic children was not significant at group homes, institutions, and supervised independent living, whereas the variable non-Hispanic White was not significant at foster family homes of relatives and trial home visits. The results show that race may influence the types of foster care placement for children in foster care.

The total days that a child is in foster care is a significant explanatory factor across all placement types except for institutions. Similar to the days in foster care, the number of foster care placements is also associated with trial home visits. Supervised independent living facilities and the number of foster care placements are also significant and negatively associated. The distance variables are significant in foster care placement types. The total average distance from home and the total average distance from the last foster care placements have a standard error of zero. The coefficients for both types of distance calculations are zero or close to zero for each foster care placement type compared to non-relative foster family homes, which means that there is no relationship between distance and foster care placement type.

### 5.4.3 Foster Care Placement Type Summary

Both MLR results in Table 5-11 and Table 5-12 show similar coefficients and significance. The same factors (age, time spent in foster care, and the number of foster care placements) appear to be drivers of the first type of foster care placement or all types of foster care placements that a child experiences while in foster care compared to non-relative foster family homes. The most noticeable differences between the two models are the distance variables. Notably, the distance calculation is different. The results in Table 5-11 use the distance from the home to the first foster care placement. In contrast, Table 5-12 uses the average distance calculation between the foster care placements based on the average distance from the child's home or the average distance from the last foster care placement. The average distance from home for the foster care placement of the average distance from the last foster care placement is significant with all foster care placements. The distance between the first foster care placement group homes and supervised independent living is not significant. The standard error of all the distance models shows little random error when distance is included in understanding what influences placement type.

# 6. CONCLUSION

The importance of place is critical to understanding a person's experiences related to geography (Yuan et al., 2020). Geography has been widely used to help identify services and supports for prevention for children and families before a child needs to enter foster care (Freisthler, Bruce, et al., 2007). However, geographic methods and research are not generally applied to understanding a child's experience once they enter foster care. Assessing the population and socioeconomic neighborhood changes that a child experiences, as well as the distance that a child moves from the home, creates an opportunity to better understand a child's foster care experiences. This research contributes to the field of health geography by understanding children who are often marginalized in the foster care system and contributes to the holistic approach to helping children in foster care succeed.

This dissertation shows the importance of a foster care placement as it relates to the socioeconomic and population characteristics of the child's neighborhood before they enter foster care and while in foster care. Characteristics of the child were provided by Connecticut's DCF office, including the race and age of the child as well as details of their foster care experience, including the FDR, NYTD, Cohort 1 responses, jittered addresses of the child's home and foster care placement, the days spent in foster care, the number of foster care placements, and the foster care placement type. The information used in this dissertation is the beginning of understanding the geographic impact of children in foster care.

The geographic placement stability of children in foster care is multifaceted with effects on (1) neighborhood characteristics, (2) children's foster care outcomes related to their FDR, (3) transition to adulthood for youth who age out of foster care, and (4) types of foster care placements. When foster care agencies are implementing measures to create geographic placement stability based on the four areas of this dissertation, they should consider the importance of the foster care placement. This research builds on previous studies that examine the neighborhood predictors linked to foster care (Huang et al., 2016) and uses various statistical and geospatial methods to understand how geography affects the outcomes of children in foster care.

Social work defines itself by using a person-in-environment lens; adding an understanding of geography creates an important method to enable the field to better support positive outcomes for children and families. Currently, most of the social work research related to geography has been primarily focused on the prevention of children entering foster care. However, this research shows that once the child is in foster care, wraparound services and greater attention to the change of environment that a child has will lead to better outcomes for children in the foster care system. In general, the socioeconomic variables were more likely to be significant in the models based on the placement Census tract instead of the home Census tract. The results of the analysis show that the location of the foster care placement matters more than the location of the child's home before they enter foster care when examining the days a child spends in foster care, the number of foster care placements, the distance from home, and positive FDRs, which include adoption, guardianship, living with a relative, or reunifying with their family.

The negative binomial and OLS models examine the population factors of the home and the placement Census tracts and the absolute value change of the home and the placement Census tract. Three different sets of dependent variables were used to understand the population factors, including the days in foster care, the number of foster care placements, and distance (from the home Census tract and from the placement Census tract). The different analyses show that where a child is placed impacts their outcomes in foster care, more so than the location of the child's home before they entered foster care. The importance of placement over the child's home when it comes to children's foster care experiences (days in care, number of placements, and distance from placement(s)) should be considered by foster care agencies when placing a child in foster care.

Service delivery for children in foster care is particularly important for children's well-being. When child welfare agencies incorporate geographic placement considerations as part of their permanency planning, they need to understand the importance of the neighborhood characteristics of the foster care placement. These decisions must be in concert with the judges and caseworkers when considering the availability of foster care placements to ensure a child's success. Many child welfare agencies focus on prevention services and target areas that report a high number of cases to CPS, particularly around poverty (Freisthler, Gruenewald, et al., 2007). However, the results of the population factors show that the socio-economics variables were not significant factors in the child's home Census tract before they entered foster care related to the days a child spends in foster care. This shows that efforts to provide preventative services based on the neighborhood's socioeconomic status may not be the most efficient place to locate and focus resources. Child welfare agencies should also consider maintaining hot spot maps to understand where children are being placed and where the child's home was before they entered foster care. Identifying hot spots where children spend more days in foster care or have a higher number of foster care placements in their communities. These maps can be used as a tool for child welfare agencies to use geographic models to precisely allocate future services for children and families in the foster care system.

Foster care outcomes for this dissertation were examined first by looking at the FDR of the child when they exited foster care with hierarchal modeling and second by the NYTD outcomes with the logistic regression. The FDR that a child has when they exit foster care is based on whether they achieved permanency through adoption, guardianship, living with other relatives, or reunifying with their family. The hierarchal model first considered the location of the child's home when they entered foster care and the location of the foster care placement. None of the socioeconomic and population factors in the hierarchal models for a child's home before entering foster care are significant factors.

The hierarchal model's result for the location of the foster care placement is similar to the population factors model that examined the days a child spends in foster care and the number of foster care placements. This reiterates that a child's foster care placement is a key factor that should be considered when placing a child to ensure a positive FDR. Child welfare agencies should consider these results when recruiting foster families, planning for resources for children entering foster care, and maintaining a stable environment for children by identifying neighborhoods where a child can thrive. This dissertation shows that the level of urbanicity of a neighborhood is a driver of the days a child spends in foster care based on the location of the foster care placement.

The logistic regression results are the subset of this dissertation's foster care population based on whether the youth(s) were eligible to participate in the NYTD survey based on the federal regulation. There are several limitations to using the cohort-1 NYTD survey since states were generally challenged in collecting the youth outcome data as it was the first year the survey was administered to older youth in foster care. Yet, Connecticut's participation rates for 17 year old's were higher than the national average, and their participation rates in 2011 in the bottom top third of all the states (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2018).

The logistic regression results found that when a child is placed closer to their home, they are more likely to be incarcerated or participate in high-risk behaviors. This result differs from the other models in this dissertation since the NYTD survey focuses on only older youth. The effect of distance from a child's home needs further study on children aging out of foster care with multiple cohorts of NYTD surveys. Additional information on the youth who participated in the NYTD survey may help explain the survey results, such as juvenile court records and behavioral health records. This finding may also be related to how the survey question is asked. For example, homelessness is based on the youth's perception of what being homeless is, whereas a caseworker or an adult identified a reason for the youth to have been incarcerated or referred for treatment related to risky behavior. Additionally, youth at the age of 17 are more mobile and have the ability to get around easier than younger children, which may influence some of the behavioral results related to risky behavior or incarceration. Child welfare agencies should be providing support for these youth, such as helping youths acquire a driver's license and learn to navigate transportation systems.

The last set of analyses is based on MLR, which focuses on the type of foster care placement. The type of foster care placement has similar drivers based on the child's age, time spent in foster care, and the number of foster care placements between the first type of foster care placement or all types of foster care placements that a child experiences while in foster care compared to non-relative foster family homes. The most noticeable differences between the two models are the significance of the distance variables. The average distance from home for the foster care placement and the average distance from the last foster care placement are significant with all foster care placements. The MLR results show that distance is particularly important at the first foster care placement and for all foster care placements for foster family home relatives. This result may be driven by families living in the same neighborhoods and willingness to care for a child.

Foster care placements that are at group homes and institutions are typically associated with children or youth who have experienced delinquency (Ryan et al., 2008). Youth who experience delinquency or other behavioral outcomes may have fewer options for available types of foster care placements, creating less of a need to understand geographic proximity. Additional case records on the child's needs and availability on the foster care placements may explain why foster care placements are chosen. Child welfare agencies should strive to incorporate cohesion through geographic placements by working with the youth to access transportation or services that could keep them connected to their familiar environment.

Additional research is needed to support these findings, such as qualitative interviews with the children focusing on the distance between foster care placement and change in the neighborhood. Interviews with the children could support these findings on what children emotionally experience with the geographic changes of each foster care placement. Focus groups of youth and how their identity and views are changed with each foster care placement could assist states in developing practices to keep children in neighborhoods where they feel most comfortable residing. States could develop policies from former youth with lived experience in the foster care system about finding long-term placements that reflect the child's identity within their foster care placements.

Many states have laws supporting keeping a child close to home. However, the practice of keeping a child close to home is typically restricted to school districts. In states where school districts are county-administered and large in both geography and population, keeping a child in a school district may not be enough to keep a child geographically close to home. Understanding the geography of where children are placed in the foster care system will lead to better outcomes and better decisions when children are faced with multiple foster care placements. The analysis in this dissertation will allow Connecticut and other child welfare agencies to make informed decisions on geographic placement stability when children have multiple foster care placements and understand how these multiple moves and the distance between these moves impact children's foster care outcomes.

# APPENDIX A – CONNECTICUT LAWS

| | |
|---|---|
| **Reasonable Efforts** | **Citation: Gen. Stat. § 46b-129**<br>**The term 'reasonable efforts' refers to the services to be provided to the parents and the steps the parents may take to address the problems that prevent the child from safely reuniting with the parents.**<br>**Citation: Gen. Stat. §§ 46B-129; 17a-111b**<br>The Department of Children and Families must make reasonable efforts to keep the child or youth with his or her parents prior to the issuance of an order to remove the child from the home. If the child is removed from the home, reasonable efforts must be made to achieve the goals of the permanency plan.<br>The Commissioner of Children and Families shall make reasonable efforts to reunify a parent with a child unless the court (1) determines that such efforts are not required pursuant to § 17a-111b(b) or § 17a-112(j), or (2) has approved a permanency plan other than reunification pursuant to § 46b-129(k). (Child Welfare Information Gateway, 2020b) |
| **Placement of Children with Relatives** | **Citation: Ann. Stat. § 17a-101m**<br>Immediately upon the removal of a child from the custody of the child's parent or guardian pursuant to § 17a-101g(e) or § 46b-129, the Department of Children and Families shall exercise due diligence to identify all grandparents and other adult relatives of the child, including any adult relatives suggested by the parents, subject to exceptions due to family or domestic violence. Ann. Stat. § 17a-101m. (Child Welfare Information Gateway, 2018b) |
| **Best Interest of the Child** | **Citation: Gen. Stat. § 45a-719**<br>'Best interests of the child' shall include, but not be limited to, a consideration of the age of the child, the nature of the relationship of the child with his or her caregiver, the length of time the child has been in the custody of the caregiver, the nature of the relationship of the child with the birth parent, the length of time the child has been in the custody of the birth parent, any relationship that may exist between the child and siblings or other children in the caregiver's household, and the psychological and medical needs of the child. The determination of the best interests of the child shall not be based on a consideration of the socioeconomic status of the birth parent or the caregiver. (Child Welfare Information Gateway, 2020a) |
| **Extended Foster Care** | **Citation: Conn. Gen. Stat. § 46b-129(j)(5)**<br>Youth may remain in care until age 21, with the youth's consent, if youth is (A) enrolled in a full-time approved secondary education |

| | |
|---|---|
| | program or an approved program leading to an equivalent credential; (B) enrolled full time in an institution which provides postsecondary or vocational education; or (C) participating full time in a program or activity approved by the commissioner designed to promote or remove barriers to employment. Commissioner has discretion to waive requirements (A)-(C) based on compelling circumstances.(Juvenile Law Center, 2020). |
| **Re-Entry Eligibility and Procedure** | **Citation: Dep't of Children & Fam. Servs., Policy Manual, Policy No. 42-8 (2015); see also Dept' of Children & Fam. Servs, Adolescent Servs. Best Practices Guide 55-58 (2015)**<br>The Department allows re-entry for educational or vocational or employment services which can lead to gainful employment. Youth may re-enter care if youth (1) was committed as abused, neglected or uncared, or dually committed, at the time of his or her 18th birthday; (2) left care after age 18, but before age 21, and did not participate in two post-secondary education or employment training programs; (3) has had his or her case closed for at least 90 days in LINK, or has had services discontinued for at least 90 days; (4) has proof of an educational plan or employment, including transcripts, certificates, report cards, proof of enrollment or acceptance or start date letters; (5) is not married; and (6) is not on active duty with any of the armed forces of the United States. If a youth has not attained a secondary school diploma and is pursuing a GED, approval from the Commissioner or Regional Administrator or designee shall be required for re-entry. A youth who has been approved to attend a GED program shall be required to accept additional support services that may include tutoring, in order for the youth to complete the GED in six months. (Juvenile Law Center, 2020). |

## APPENDIX B - HIERARCHICAL MODEL UNDERLYING EQUATIONS

Hierarchical Linear Model (Zhang, 2015):

**Level-1 (Within-unit) models:**

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij}) + r_{ij} \; with \; E(r_{ij}) = 0 \; and \; var(r_{ij}) = \sigma^2$$

- $Y_{ij}$: **dependent variable** measured for *ith* level-1 unit nested within the *jth* level-2 unit
- $X_{ij}$: **value on the level-1 predictor**
- $\beta_{0j}$: **intercept** for the *jth* level-2 unit
- $\beta_{1j}$: **regression coefficient** associated with $X_{ij}$ for the *jth* level-2 unit
- $r_{ij}$: **random error** associated with the *ith* level-1 unit nested within the *jth* level-2 unit

**Level-2 (between-unit) models**: the level-1 regression coefficients ($\beta_{0j}$and$\beta_{1j}$) are used as outcome variables and related to each of the level-2 predictors.

$$\beta_{0j} = \gamma_{00} + \gamma_{01}G_j + U_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}G_j + U_{1j}$$
$$with \; E(U_{oj}) = 0, E(U_{1j}) = 0, E(\beta_{0j}) = \gamma_{00}, E(\beta_{ij}) = \gamma_{10},$$
$$var(\beta_{0j}) = var(U_{0j}) = \tau_{00}, var(\beta_{1j}) = var(U_{1j}) = \tau_{11},$$
$$cov(\beta_{0j}, \beta_{1j}) = cov(U_{0j}U_{1j}) = \tau_{01}, and \; cov(U_{0J}, r_{ij}) = cov(U_{1J}, r_{ij}) = 0$$

- $\beta_{0j}$: **intercept** for the *jth* level-2 unit
- $\beta_{1j}$: **slope** for the *jth* level-2 unit
- $G_j$: **value on the level-2 predictor**
- $\gamma_{00}$: **overall mean intercept** adjusted for G
- $\gamma_{01}$: **overall mean intercept** adjusted for G
- $\gamma_{10}$: **regression coefficient** associated with G relative to **level-1 intercept**
- $\gamma_{11}$: **regression coefficient** associated with G relative to **level-1 slope**
- $U_{0j}$: **random effects** of the *jth* level-2 unit adjusted for G on the **intercept**
- $U_{1j}$: **random effects** of the *jth* level-2 unit adjusted for G on the **slope**

**A combined (two-level) model**: substitute level-2 model into level-1 model
$$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + \gamma_{01}G_j + \gamma_{11}G_jX_{ij} + U_{1j}X_{ij} + U_{0j} + r_{ij}$$

"The combined model incorporates the level-1 and level-2 predictors **($X_{ij}$and$G_j$)**, a cross-level term **($G_jX_{ij}$)** as well as the composite error **($U_{1j}X_{ij}+U_{0j}+r_{ij}$)**. The two-level model is often termed a mixed model because it includes both fixed and random effects. The terms $\mathbf{U_{0j}}$ **and** $\mathbf{U_{1j}}$ demonstrate that there is dependency among the level-1 units nested within each level-2 unit, and may have different values within level-2 units, leading to heterogeneous variances of the error terms" (Zhang, 2015).

## APPENDIX C – NYTD SURVEY QUESTIONS

1. Currently, are you employed full-time?

   Yes No Declined

2. Currently, are you employed part-time?

   Yes No Declined

3. In the past year, did you complete an apprenticeship, internship, or other on-the-job training, either paid or unpaid?

   Yes No Declined

4. Currently, are you receiving social security payments (Supplement Security Income (SSI), Social Security Disability Insurance (SSDI), or dependents' payments?)

   Yes No Declined

5. Currently, are you using a scholarship, grant, stipend, student loan, voucher, or other types of educational, financial aid to cover any educational expenses?

   Yes No Declined

6. Currently, are you receiving any periodic and/or significant financial resources or support from another source not previously indicated and excluding paid employment?

   Yes No Declined

7. What is the highest educational degree or certification that you have received?

   Drop Down Box

8. Currently, are you enrolled in and attending high school, GED classes, post-high school, vocational training, or college?

    Yes  No  Declined

9. Currently, is there at least one adult in your life, other than your caseworker, to whom you can go for advice or emotional support?

    Yes  No  Declined

10. Have you ever been homeless?

    Yes  No  Declined

11. Have you ever referred yourself, or has someone else referred you for an alcohol or drug abuse assessment or counseling?

    Yes  No  Declined

12. Have you ever been confined in a jail, prison, correctional facility, juvenile, or community detention facility in connection with allegedly committing a crime?

    Yes  No  Declined

13. Have you ever given birth or fathered any children that were born?

    Yes  No  Declined

14. If you responded yes to the previous question, were you married to the child's parent at the time each child was born?

    Yes  No  Not Applicable  Declined

15. Currently, are you on Medicaid?

    Yes  No  Declined

16. Currently, do you have health insurance other than Medicaid?

Yes No Not Applicable Declined

17. Does your health insurance include coverage for medical services?

    Yes No Not Applicable Declined

18. Does your health insurance include coverage for mental health services?

    Yes No Don’t Know Not Applicable Declined

19. Does your health insurance include coverage for prescription drugs?

    Yes No Don’t Know Not Applicable Declined

Only for 19 and 21-year-olds who are no longer in foster care.

20. Currently, are you receiving ongoing welfare payments from the government to support your basic needs?

    Yes No Don’t Know Not Applicable Declined

21. Currently, are you receiving public food assistance?

    Yes No Don’t Know Not Applicable Declined

22. Currently, are you receiving any sort of housing assistance from the government, such as living in public housing or receiving a housing voucher?

    Yes No Don’t Know Not Applicable Declined

# APPENDIX D – COMBINED MULTINOMIAL REGRESSION RESULTS FOR DAYS IN FOSTER CARE AND NUMBER OF PLACEMENTS

| | | | | | | Reduced by Lasso | | Reduced by Lasso | |
|---|---|---|---|---|---|---|---|---|---|
| | | Days in Care | | Number of Placement | | Days in Care | | Number of Placements | |
| | Source | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) |
| Home Census Tract | (Intercept) | 6.45* | 0.03 | 1.42* | 0.02 | 6.50* | 0.02 | 1.43* | 0.02 |
| | % Hispanic | 0.02 | 0.04 | -0.02 | 0.02 | | | | |
| | % Non-Hispanic Black | -0.19* | 0.03 | -0.06* | 0.02 | -0.06* | 0.02 | -0.01 | 0.02 |
| | % Under 18 | 0.04 | 0.08 | 0.12* | 0.05 | 0.06 | 0.07 | 0.09 | 0.05 |
| | % Urban | 0.03 | 0.02 | 0.01 | 0.01 | | | | |
| | % on Public Assistance | -0.29* | 0.10 | -0.17* | 0.07 | -0.32* | 0.10 | -0.19* | 0.06 |
| | % Below Poverty | -0.07 | 0.06 | 0.07 | 0.04 | -0.12* | 0.05 | 0.03 | 0.03 |
| | % Unemployed | -0.02* | 0.19 | 0.02 | 0.13 | | | | |
| Placement Census Tract | % Hispanic | -0.06 | 0.04 | 0.00 | 0.03 | -0.12* | 0.03 | -0.04 | 0.02 |
| | % Non-Hispanic Black | 0.09* | 0.03 | 0.10* | 0.02 | 0.20* | 0.03 | 0.13* | 0.02 |
| | % Under 18 | 0.28* | 0.09 | -0.16* | 0.06 | 0.34* | 0.09 | -0.14* | 0.06 |
| | % Urban | 0.12* | 0.02 | -0.01 | 0.01 | 0.09* | 0.01 | -0.01 | 0.01 |
| | % on Public Assistance | 0.12 | 0.10 | 0.32* | 0.07 | -0.04* | 0.09 | 0.23* | 0.06 |
| | % Below Poverty | -0.11 | 0.06 | -0.09* | 0.04 | | | | |
| | % Unemployed | -0.93 | 0.19 | -0.54* | 0.13 | -1.02* | 0.19 | -0.57* | 0.13 |
| Absolute Value of Census | % Hispanic | 0.09* | 0.03 | -0.02 | 0.02 | | | | |
| | % Non-Hispanic Black | 0.27* | 0.03 | 0.10* | 0.02 | | | | |
| | % Under 18 | 0.39* | 0.09 | 0.07 | 0.06 | 0.42 | 0.09 | 0.05 | 0.06 |
| | % Urban | 0.03 | 0.02 | 0.00 | 0.01 | | | | |
| | % on Public Assistance | 0.33* | 0.10 | 0.10 | 0.07 | 0.43 | 0.10 | 0.13 | 0.07 |
| | % Below Poverty | 0.08 | 0.05 | 0.10* | 0.04 | 0.19 | 0.05 | 0.10 | 0.03 |
| | % Unemployed | 0.49* | 0.18 | -0.33* | 0.12 | 0.80 | 0.15 | -0.25 | 0.10 |
| | Log likelihood | 268.74* | | 95.312*** | | -214.34* | | -80.51* | |

< *0.05

## APPENDIX E – COMBINED OLS REGRESSION FOR DISTANCE

| | | | | | | Reduced by Lasso | | Reduced by Lasso | |
|---|---|---|---|---|---|---|---|---|---|
| | | Distance From Home | | Distance From Placement | | Distance From Home | | Distance From Placement | |
| | Source | *B* | (SE) | *B* | (SE) | *B* | (SE) | *B* | (SE) |
| Home Census Tract | (Intercept) | 6.45* | 0.03 | 28.23* | 1.02 | 12.03* | 0.41 | 27.55* | 0.58 |
| | % Hispanic | 0.02 | 0.04 | -4.36* | 0.92 | | | | |
| | % Non-Hispanic Black | -0.19* | 0.03 | -6.09* | 0.70 | -0.83* | 0.41 | -5.58 | 0.59 |
| | % Under 18 | 0.04* | 0.08 | 4.85* | 1.95 | 6.80* | 1.28 | 4.43 | 1.82 |
| | % Urban | 0.03* | 0.02 | -4.38* | 0.60 | | | | |
| | % on Public Assistance | -0.29* | 0.10 | -10.1* | 2.49 | 9.54* | 1.67 | -7.36* | 2.39 |
| | % Below Poverty | -0.07* | 0.06 | 6.46* | 1.31 | 8.23* | 0.83 | 2.18 | 1.18 |
| | % Unemployed | -0.02* | 0.19 | 36.88* | 4.46 | | | | |
| Placement Census Tract | % Hispanic | -0.06* | 0.04 | -3.2* | 0.91 | -0.90 | 0.58 | -1.99* | 0.83 |
| | % Non-Hispanic Black | 0.09* | 0.03 | -9.66* | 0.65 | -4.30* | 0.47 | -9.79* | 0.67 |
| | % Under 18 | 0.28 | 0.09 | 4.89* | 2.13 | -2.21 | 1.52 | 3.81 | 2.16 |
| | % Urban | 0.12* | 0.02 | -6.05* | 0.58 | -2.61* | 0.24 | -7.52* | 0.35 |
| | % on Public Assistance | 0.12 | 0.1 | -12.8* | 2.57 | 10.05* | 1.56 | -5.75* | 2.22 |
| | % Below Poverty | -0.11* | 0.06 | 5.86* | 1.33 | | | | |
| | % Unemployed | -0.93* | 0.19 | 31.2* | 4.71 | 6.63* | 3.36 | 36.06* | 4.79 |
| Absolute Value of Census | % Hispanic | 0.09* | 0.03 | -0.4 | 0.79 | | | | |
| | % Non-Hispanic Black | 0.27* | 0.03 | -0.47* | 0.68 | | | | |
| | % Under 18 | 0.39* | 0.09 | -13.06* | 2.09 | -28.22* | 1.53 | -12.64* | 2.17 |
| | % Urban | 0.03* | 0.02 | 1.82* | 0.58 | | | | |
| | % on Public Assistance | 0.33* | 0.10 | 0.54* | 2.46 | -16.68* | 1.71 | -1.43 | 2.44 |
| | % Below Poverty | 0.08* | 0.05 | -6.84* | 1.27 | -10.50* | 0.86 | -8.07* | 1.22 |
| | % Unemployed | 0.49* | 0.18 | -30.1* | 4.27 | -32.63* | 2.65 | -12.61* | 3.78 |
| | F-Statistic | 121.6 | | 96.3 | | 180.8 | | 127.7 | |
| | $R^2$ | 0.07 | | 0.04 | | 0.06 | | 0.04 | |

< *0.05

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