MATHEMATICA Policy Research

casey family programs

REPORT

FINAL REPORT

Superutilization of Child Welfare, Medicaid, and Other Services

March 29, 2018

Mathematica Policy Research
Elizabeth Weigensberg
Derekh Cornwell
Lindsey Leininger
Matthew Stagner
Sarah LeBarron
Jonathan Gellar
Sophie MacIntyre
Richard Chapman

Casey Family Programs
Erin J. Maher
Peter J. Pecora
Kirk O'Brien

Submitted to:
Casey Family Programs
2001 Eighth Avenue Suite 2700
Seattle, WA 98121

Project Officer: Erin Maher
Contract Number: FY16-0079/SCHEDULE 2

Submitted by:
Mathematica Policy Research
111 East Wacker Drive, Suite 920
Chicago, IL 60601-4303
Telephone: (312) 994-1002
Facsimile: (312) 994-1003

Project Director: Elizabeth Weigensberg
Reference Number: 50222

This page has been left blank for double-sided copying.

ACKNOWLEDGEMENTS

This work was conducted in collaboration with Casey Family Programs, whose mission is to provide, improve, and, ultimately, prevent the need for foster care. We thank Linda Jewell Morgan and Fred Simmens of the Casey Family Programs' Strategic Consulting Team for their collaboration and work with the sites. We thank our senior project advisors Toni Rozanski of Casey Family Programs and Nadia Sexton. We also think our outside expert reviewers, Richard Thompson of the Juvenile Protection Association, Brett Drake of Washington University in St. Louis, Mary Armstrong of the University of South Florida, and Laura Nolan from Mathematica Policy Research.

The project was made possible through the partnership and contributions of many people and organizations in our study sites. We thank our site partners, including the Tennessee Department of Children's Services, TennCare, the Florida Department of Children and Families, the Florida Agency for Healthcare Administration, and Eckerd Kids, the lead Community Based Care agency in Hillsborough, Pinellas, and Pasco Counties, for their engagement in the study to share data, help refine the data questions, interpret the results, and identify ways in which they could use the findings to inform policy and program design.

Lastly, this research would not have been possible without the contributions of many other Mathematica Policy Research staff. The authors would like to thank Christina Alva, Stephanie Barna, Daniel Kassler, Brenda Natzke, Jessica Nysenbaum, Matt Mleczko, Kelley Monzella, Nora Paxton, Liz Potamites, Dmitriy Poznyak, Christine Ross, Michael Sinclair, and Fei Xing.

This page has been left blank for double-sided copying.

DISCLAIMER

This publication was derived in part from a data set supplied by the Florida Agency for Health Care Administration, which specifically disclaims responsibility for any analysis, interpretations, or conclusions that may be created as a result of the data set. Data for this project were also provided by Florida Department of Children and Families according to the specifications requested by Mathematica Policy Research. All analysis of data was completed by Mathematica Policy Research. Interpretation of results and identification of implications were informed by input from Mathematica Policy Research, Casey Family Programs, and the site partners. The findings and conclusions presented in this report are those of the authors alone, and do not necessarily reflect the opinions of Casey Family Programs or site partners.

This page has been left blank for double-sided copying.

CONTENTS

This page has been left blank for double-sided copying.

TABLES

FIGURES

I. INTRODUCTION

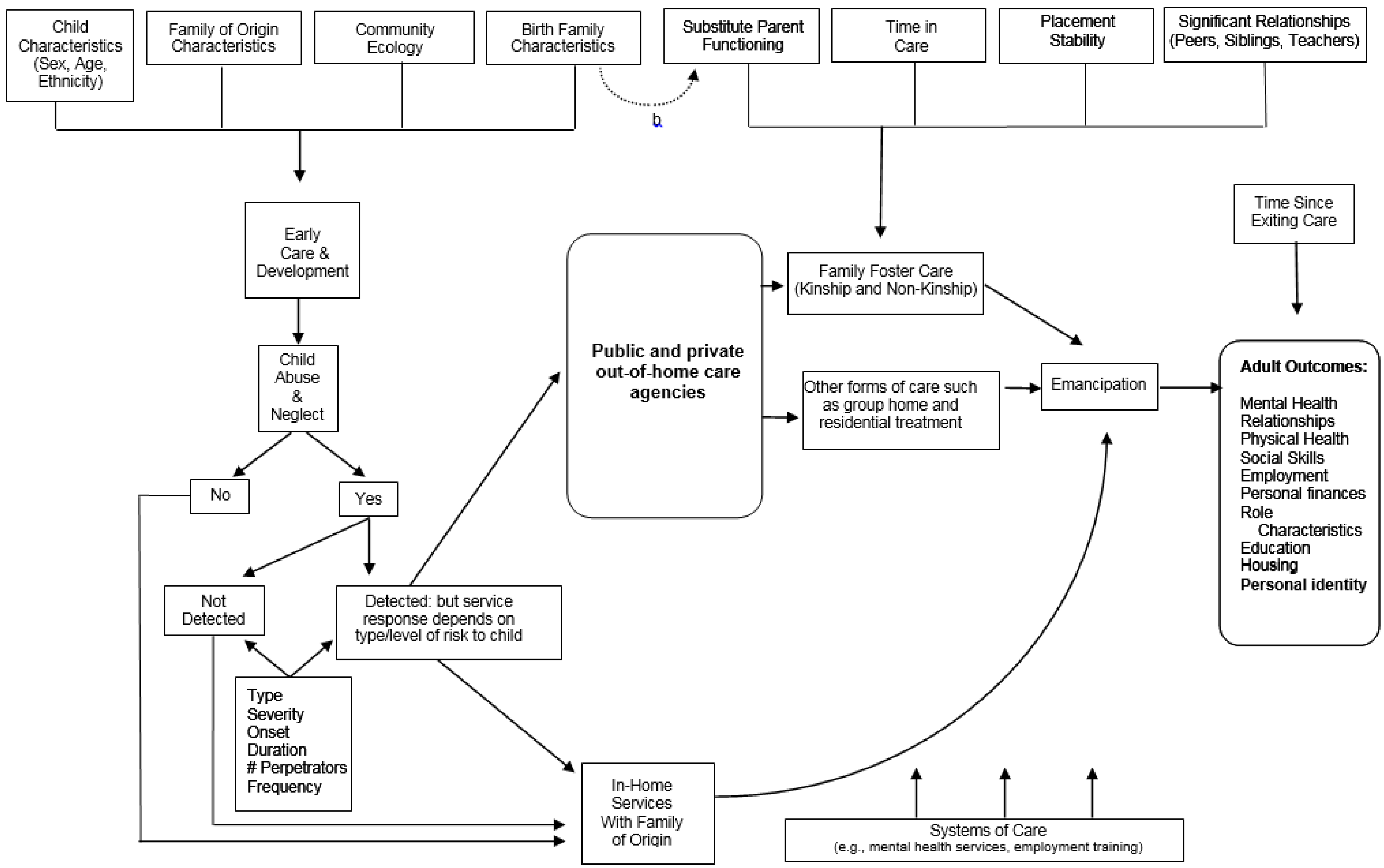
Each year in the United States, community members report hundreds of thousands of children to the child welfare system due to suspected abuse or neglect. Approximately 12 to 13 percent of children will be a confirmed victim of maltreatment during their childhood (Wildeman et al. 2014). Approximately 1.3 million children annually receive services from a child welfare agency following a report of child maltreatment. In 2016, 203,582 of these children entered into foster care (DHHS 2018). At the end of federal fiscal year 2016, 437,465 children were in foster care (DHHS 2017). In addition to receiving child welfare services, children placed in foster care are eligible for Medicaid. Although these children represent only 3 percent of all children receiving Medicaid, they account for 15 percent of those receiving Medicaid behavioral health services (Allen and Hendricks 2013).

Children and families involved with child welfare often have an acute need for health, mental health, substance abuse, and other services to ensure a safe and nurturing environment. Although children taken into child welfare custody are eligible for Medicaid to assist with their medical needs, there is often a gap between service need and receipt (Maher et al. 2016). As a result, there is a critical need for information about how child welfare agencies, Medicaid agencies, and related services come together to support the needs of these children and their families, and about whether alternative interventions at key points could prevent children and families from becoming high users of these services. Therefore, to capture a fuller array of services that children in foster care receive, it is necessary to combine Medicaid and child welfare services data. By identifying and describing patterns of high service use *across* both Medicaid and child welfare systems, agencies can provide more tailored and effective services sooner to better meet the needs and improve outcomes for children in foster care.

A. Theoretical foundation

This study is informed by a number of theoretical or conceptual models, such as Bronfenbrenner's ecology of child development (Bronfenbrenner 1979; Bronfenbrenner and Morris 1998). Another conceptual model is summarized in the Developmental Framework (Figure I.1) for understanding child development for youth placed in Foster Care. This figure highlights many of the important factors that affect long-term foster care, including family of origin characteristics, community ecology, and significant relationships – as well as poverty and institutional, relational, and individual factors that can affect health, mental health, and development in the long run. The study's analytic models were informed by these frameworks.

Figure I.1. Developmental Framework for Understanding Child Development for Youth Placed in Foster Care[a]



[a] Adapted from Pecora, P.J., Kessler, J. Williams, A.C. Downs, D.J. English, J. White, and K. O'Brien. *What works in Family Foster Care? Key Components of Success from the Northwest Foster Care Alumni Study*. New York and Oxford, England: Oxford University Press, 2010, p. 42; and Landsverk et al. (1995). For more information, please contact researchteam@casey.org at Casey Family Programs.

[b] Birth families often influence foster parent service delivery and functioning (e.g., visitation).

B. Study objectives

To address the need to better understand characteristics of high service users ("superutilization") in child welfare, this study uses administrative data from child welfare, Medicaid, and substance abuse and mental health to identify children in out-of-home child welfare custody who experience superutilization. High service use may be appropriate for those with complex needs; however, it may also be indicative of children and families not getting the right types of support at critical junctures, being placed in overly restrictive placements, receiving ineffective services, or having extensive needs that should be met in other ways. By identifying subpopulations of children and youth who have high service use, we can identify more effective ways to serve them.

The study addresses the following research questions:

1. What is superutilization of child welfare and other services? What are the distinguishing characteristics of children who experience superutilization of child welfare and other services?
2. Are there different types of superutilization? Specifically, are there types of superutilization based on frequency, duration, intensity, or cost of services?
3. What characteristics of children at the time of child welfare involvement—specifically at the time of entry into out-of-home care—predict superutilization?

Answers to the questions above can help child welfare and Medicaid agencies develop more-effective, targeted, and timely service delivery to better meet the needs of children and families while reducing service costs. Ultimately, by better understanding the characteristics of superutilization, agencies will be able to identify and better serve families before intensive services are required.

C. Background

Health care systems, in particular, recognize that a small number of program participants can have a disproportionate impact on overall program costs. Often, these patients have complex service needs. Less is known about what specifically their needs are, variation within a high service use population, and different drivers of high service use. Health care analysts seek answers through identification of the "superutilization" of services, and ideally, once identified, program managers design interventions to better serve their needs, improve outcomes, and save costs (Mancuso 2015).

In child welfare, the same identification of superutilization of services can be used to improve service delivery and save costs, though this approach has been used less frequently than in health care. Since children in foster care are categorically eligible for Medicaid and also receive some services through child welfare agencies, identifying high service users in this population requires merging these data sets to create an accurate picture of overall service use.

Children in foster care already account for a disproportionate amount of Medicaid services and costs (Allen and Hendricks 2013; Medicaid and CHIP Payment and Access Commission 2015). Within this population, potential exists to examine high service users within and across both Medicaid and child welfare. To our knowledge, few studies have done so. A seminal study on chronic neglect (or frequently encountered families) in a single state, estimated that while comprising 20% of the child welfare population, they accounted for half of all spending (Loman 2006). A study in another state examined demographic and other characteristics of higher mental health Medicaid expenditures among children in out-of-home care (Clark and Yampolskaya 2011). These studies, while relevant, have not taken the approach of universally identifying the high service users and then describing their characteristics or multiple pathways to high service use as this study does in a comprehensive, multidimensional way.

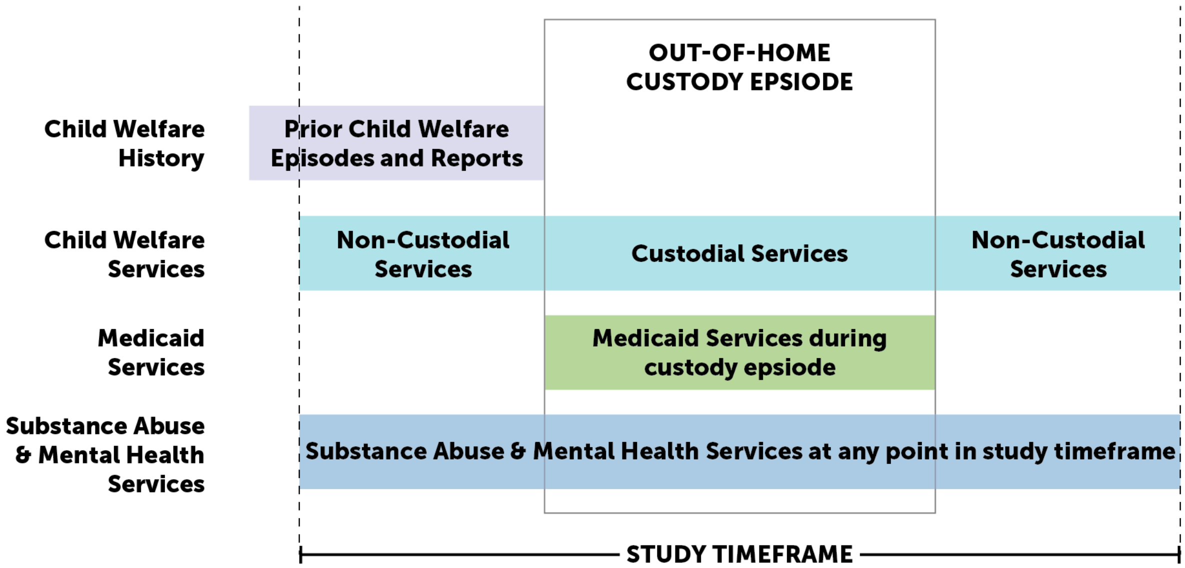
D. Study approach and conceptualization of superutilization

Building on the theoretical foundation referenced above, more research is needed to better understand superutilization of services provided for children in foster care. Therefore, this study serves as a key step toward empirically examining superutilization among children in the child welfare system, who spend time in out-of-home custody, including types and predictors of superutilization. In this respect, the study is exploratory and requires a flexible approach to measurement and model specification. Below, we discuss the types of services that are examined in this study and elaborate on our conceptual approach to defining superutilization. In particular, we focus on the broader concept of superutilization and then address the multiple dimensions that relate to it.

1. Types of services examined in this study

Children in the child welfare system often receive services from several service sectors in addition to child welfare agencies and their contracted providers, which may also be dependent on whether they are in out-of-home child welfare custody. Specifically, children in child welfare custody are eligible for and receive health services from Medicaid. In some states, they may also receive other mental health and substance use services that are not covered by Medicaid but are funded by other public resources. Given the importance of each of these types of services for children in child welfare, this study aims to assess service utilization among them. The types of services included as part of this study are depicted in Figure I.2.

Figure I.2. Types of services included in the study of superutilization



The primary focus of this study is on children who are in child welfare custody *and* were placed in out-of-home settings—that is, children who were removed from their homes and placed in foster care. Given the importance of child welfare history, such as prior child welfare custody episodes and reports, we include all available information as part of the study. Because we received complete child welfare histories in regard to prior reports and custody episodes from our child welfare data partners, we include this information even if they occurred before the study timeframe. In regard to child welfare services, we primarily focus on receipt of services during the out-of-home custody episode, but also consider any in-home services, also referred to as non-custodial services, that may have been received by those prior to or after the out-of-home custody episode. Although not the focus of the current study, some children only received in-home services and never had an out-of-home custody episode. Future research may want to investigate superutilization among an in-home service population of child welfare-involved families.

This study is focused solely on the out-of-home care population of children because they are eligible for Medicaid services given their custody status, and for which we were able to make a sufficient match with Medicaid data. Children who are removed from their homes and placed in child welfare custody are eligible for Medicaid for the duration of time spent in custody. Therefore, this study includes Medicaid services received during the time in which the child was in child welfare custody. Our measurement of service utilization does not include Medicaid services that may have been received before or after the custody episode, given uncertainty regarding Medicaid eligibility during those times. The study looks at three types of Medicaid services: inpatient, outpatient, and emergency services. For each type of Medicaid service, we included both behavioral and physical health services.

Lastly, for one of the two study sites, we were able to assess non-Medicaid mental health and substance use services that are also available to children and funded by the state. Given that eligibility for these services is not necessarily tied to child welfare custody, we include any available services during the study time period. Further details on the specific partners and data included in the study are discussed in Section I.E.

2. Definition and dimensionality of superutilization

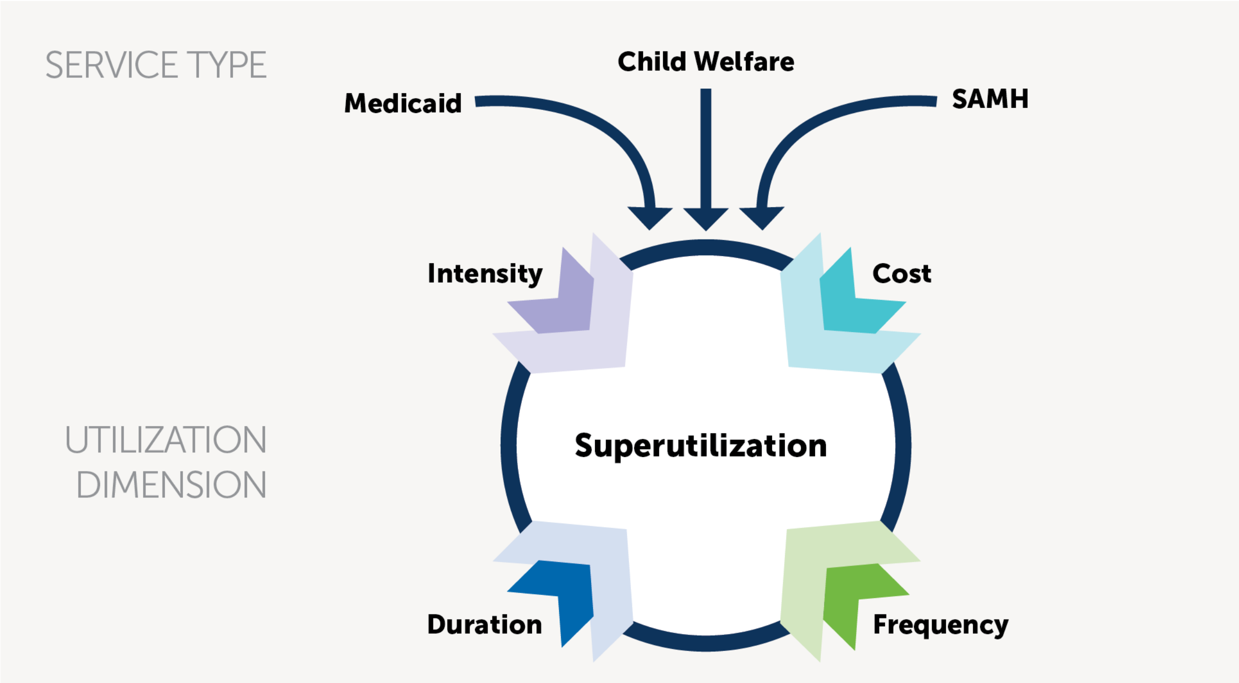
High service use, or superutilization of services as we refer to it in this study, is a complex concept that includes multiple dimensions of service use and requires identifying a threshold of use that distinguishes those receiving more than typical service use and experiencing superutilization.

Determining how to identify a threshold for superutilization is an important consideration in terms of operationalizing the concept for analysis. Deciding how to place the meaning of "high service use" in proper context, however, is equally important for policy and analytical reasons. In some cases, the definition of high service use may be based on exceeding an absolute threshold value, such as an absolute dollar amount or number of services. Alternatively, the notion of superutilization of child welfare services may be defined relative to usage patterns among a peer group, which may differ by age. For example, if we look at durations in which children are in child welfare custody, one year in custody for a 2-year-old may be considered superutilization; however, for a 17-year-old, one year in custody may not be considered superutilization given others of this age may have experienced much longer durations in custody. In this respect, superutilization may be seen as a relative measure; we address this by using age-adjustment and annualized rates to standardize our measurement of superutilization of services. For identifying the threshold in which someone is identified as experiencing superutilization, we selected the top 10% of the distribution for each measure of service use. Further discussion of our approach to measurement of superutilization is in Chapter V.

In addition to identifying the threshold for superutilization, it is important to consider the services themselves and how we assess utilization of them. We described the types of services above (specifically, child welfare, Medicaid, and other substance abuse and mental health services), but knowing the type of service a child receives is not sufficient to establish superutilization, even though it provides important context. We must consider that superutilization is a multidimensional concept that encompasses different aspects of service use.

To account for and measure the multidimensional nature of the concept, the study team defined four core dimensions of superutilization: intensity, frequency, duration, and cost. For any given service type, superutilization may occur along one, some, or all of these dimensions. This relationship is depicted in Figure I.3 below. Specifically, the figure shows the three types of services that we examine in this study and how each can be viewed within the multidimensional framework of superutilization. In this approach, for example, it is possible for a child to experience superutilization based on the frequency of a type of service even if that child does not experience superutilization along any of the other dimensions. Therefore, we consider high utilization along any of these dimensions to be superutilization.

Figure I.3. Service type and dimensions of superutilization



Note: SAMH is Substance Abuse and Mental Health data in Florida.

The four dimensions of superutilization, depicted in Figure I.3, are discussed below.

- **Intensity.** The intensity of service receipt, in this context, refers to the level of restrictiveness of child welfare placements. In particular, we identify the extent to which children are placed in group or residential settings compared to less-restrictive home-based foster care placements.
- **Frequency.** This dimension captures the number of services used, specifically the count of services received within a defined period of time. The rationale behind this dimension is that the number of services received is indicative of high utilization patterns.
- **Duration.** The duration of service use captures the length of time over which the child is in child welfare custody. Conceptually, longer durations may be interpreted as a higher level of service within the child welfare system. Duration provides a distinct way to characterize service utilization apart from intensity and frequency. An individual service, for example, may be intense or non-intense, may occur frequently or infrequently, and may be short or long in duration.
- **Cost.** In theory, cost should capture the intensity, frequency, and duration of a service. In this respect, the cost dimension should be capable of condensing the information provided in the other three dimensions into a single summary measure based on a total dollar amount. As discussed in Chapter II, however, the cost data available for this study were limited, including incomplete cost information for many child welfare services and types of placements.

By using several dimensions of service use, as opposed to a singular measure such as cost, this research can provide a more nuanced exploratory perspective on superutilization across different types of services to inform policy and practice decisions.

E. Study scope

Using this approach to address the research questions, the study team engaged partners from two sites: (1) the state of Tennessee and (2) the three-county region of Hillsborough, Pasco, and Pinellas counties in Florida, which includes Tampa, St. Petersburg, and Clearwater. Partners from both sites agreed to participate in the study given their interest in understanding more about superutilization of child welfare, Medicaid, or other services, and the characteristics that are most associated with superutilization to help them better identify and serve families. Study partners for each site are listed in 1.1.

I.1. Data partners

Data agency	Type of agency/organization
Tennessee	
Department of Children's Services (DCS)	State agency overseeing child welfare
TennCare	State agency overseeing Medicaid
Hillsborough, Pasco, and Pinellas counties, Florida	
Office of Child Welfare, Department of Children and Families (OCW)	State agency overseeing child welfare
Substance Abuse and Mental Health Program Office, Department of Children and Families (SAMH)	Division within OCW state agency overseeing state-funded substance abuse & mental health
Agency for Health Care Administration (AHCA)	State agency overseeing Medicaid
Eckerd Kids (Eckerd)	State-contracted Community Based Care provider of purchased child welfare services in Hillsborough, Pasco, and Pinellas counties

The study scope includes children who entered out-of-home custody at any point between January 1, 2011, and December 31, 2015. The decision to focus the study scope on those in out-of-home custody was informed in part by the increased ablility to link child welfare data with Medicaid data sources among this population, which is further discussed in Chapter II. We refer to this as the "study window." As noted later in the report (II.1), availability of data sources varied within this study window and sample time frames were adjusted as a result.

As context, during the study period, TN's child welfare agency had three Commissioners, but no other major legislative or policy changes that would affect the number of children in out-of-home care. There was a media focus on child fatalities during this time period due to some child deaths from abuse or neglect. Florida also had three OCW secretaries during the study period and implemented a new safety practice model in 2013. Finally, Florida had several high profile child fatalities, which can have an impact on child welfare decision making (Jagannathan and Camasso 2017).

F. Report overview

The following chapters in the report describe the data, analysis, and findings to address the research questions.

Chapter II summarizes the data sources and key aspects of the data management, including matching procedures, construction of analytic data files, and consideration of data limitations.

Chapter III provides an overview of the study samples for each site and describes the demographic and other characteristics of the study sample along with sample members' child welfare experiences. Chapter IV summarizes service use among the study sample.

Chapter V provides a summary of the measurement considerations, definition, and identification of superutilization; Chapter VI describes the distinguishing characteristics of those children identified as experiencing superutilization of services.

Once we could identify children who experienced superutilization, we conducted latent class analysis to assess different types of superutilization. Chapter VII describes the results of the latent class analysis identifying types of superutilization for each study site. The chapter also includes a discussion of implications.

Also, we used predictive analysis to identify characteristics predictive of superutilization, at time of entry into out-of home custody. Chapter VIII provides a description of the predictive analysis results, as well as implications and applications of the results.

Lastly, Chapter IX discusses overall conclusions, limitations and implications of the study, and highlights how the study approach and findings can be informative for child welfare policy and pactice as well as for furture research in the field.

This page has been left blank for double-sided copying.

II. DATA SOURCES AND MANAGEMENT

A. Overview of study data

To study the characteristics of superutilization of child welfare, Medicaid, and other services, Mathematica requested program administrative data from multiple agencies in each of the two study sites: (1) the state of Tennessee and (2) Hillsborough, Pasco, and Pinellas counties in Florida. The research team established data use agreements with the study site partners. These agreements specified the necessary security protections and other conditions and processes that we would follow to receive and work with the data for project purposes. The data use agreements also identified the specific data needed from each study partner, specifically data on child welfare, Medicaid, and other services. II.1 summarizes the types of data requested from partners in each of the study sites, as well as the number of data files received.

II.1. Partner Agencies and Data Sources

Data agency	Type	Number of files	Time frame of data
Tennessee			
Department of Children's Services (DCS)	Child welfare data on investigations, custody, placement, services, assessments, costs	28	Jan 1, 2011–Dec 31, 2015
TennCare	Medicaid data on eligibility, prescriptions, and professional, inpatient, and outpatient claims	5	Jan 1, 2011–Dec 31, 2015
Hillsborough, Pinellas, and Pasco Counties, Florida			
Office of Child Welfare, Department of Children and Families (OCW)	Child welfare data on investigations, custody, placements	8	Jan 1, 2011–Dec 31, 2015
Substance Abuse and Mental Health Program Office, Department of Children and Families (SAMH)	Substance abuse & mental health assessments and services (non-Medicaid)	13	Jan 1, 2011–Dec 31, 2015
Agency for Health Care Administration (AHCA)	Medicaid data on eligibility, fee-for-service claims, and encounters	4	Jan 1, 2011–Dec 31, 2015
Eckerd Kids (Eckerd)	Community Based Care purchased child welfare services and costs data	16	Aug 1, 2013–Dec 31, 2015

Because agencies collected these data for program administration and management purposes, the research team needed to conduct data processing and linking activities to prepare the files for analysis. As part of this process, Mathematica researchers worked closely with program and data staff in each of the study sites to understand, accurately use, and interpret these data. In addition, given the differences in programs and policies as well as in available data across both study sites, we conducted data management and analysis separately for each of the sites. However, we discuss similarities and differences in findings across both sites when considering implications.

1. Tennessee

The Tennessee Department of Children's Services (DCS) child welfare data included 334,927 children and their families who met the study sample criteria, specifically that they either (1) were screened in and had a completed Child Protective Services (CPS) investigation or

(2) were in foster care custody or received noncustodial (in-home) child welfare services from DCS for at least one day within the time period beginning July 2011 and ending December 2015. The DCS data include a rich set of information on current and prior investigations, child welfare services, foster care placements, assessments, and costs for children in the study sample. Mathematica also received information on demographics, prior CPS involvement, and related services for parents. However, we found that most DCS services were associated with the child rather than the parent and there were limitations to the quality of parental identifying information.

In addition to the child welfare data, Tennessee's Medicaid agency, TennCare, provided five data files containing information on prescriptions, claims, and eligibility for children and their families in the DCS sample. Although TennCare provided Medicaid data for parents, fewer than 2 percent of parents in the DCS sample had valid Medicaid IDs. Because of the lack of identifying information to link Medicaid data, as well as limitations with the parent data from DCS, we focused the study scope for Tennessee on the child.

2. Hillsborough, Pasco, and Pinellas counties, Florida

There were four data partners for the Florida site: Florida's Department of Children and Families' (DCF) Office of Child Welfare (OCW), Florida's Department of Children and Families' Substance Abuse and Mental Health (SAMH) Program Office, Eckerd Kids (Eckerd), and the Agency for Health Care Administration (AHCA).

OCW provided child welfare data on CPS investigations, foster care placements, and demographics for all children who (1) were investigated for alleged abuse or neglect from January 1, 2011, through December 31, 2015, or (2) received in-home or out-of-home services at any time during this period in the state of Florida. In total, Mathematica received data on 829,765 unique children and 1,142,108 unique investigations, and was responsible for limiting the data files to the geographic region of the study (Hillsborough, Pasco, and Pinellas counties). Unlike in Tennessee, however, OCW's administrative data did not contain detailed information on child welfare services or cost, because Florida contracts with local providers to provide Commuity Based Care (CBC) purchased child welfare services. As a result, we secured an additional data partner, Eckerd Kids (Eckerd), in order to understand the types and frequency of CBC-purchased services received by children and families. We also included an additional department within DCF, the SAMH Program Office, as a data partner; this office provided data from the Substance Abuse and Mental Health Information System (SAMHIS) on state-funded substance abuse and mental health services that were used among children and parents in our study sample.

Eckerd, the contracted CBC operating agency for Hillsborough, Pasco, and Pinellas counties, provided data on child welfare services and cost. However, because one of Eckerd's contracts for the three-county region did not begin until summer 2013, they could provide detailed services and cost information for children in the OCW sample only for those receiving services after this point, nearly two and a half years into the study window. Additionally, due to limitations in the administrative data, the data files provided by Eckerd were only linkable to one another using child and/or parent name. As a result of these limitations, detailed information on CBC-purchased child welfare services and costs are minimal for the Florida sample.

The SAMH Program Office provided data on mental health and substance abuse services for both children and their parents in Florida from SAMHIS. Mathematica received data for almost 3,000,000 individuals and linked them to the study sample.

AHCA provided Medicaid claims, encounters, and eligibility information for all individuals enrolled in Medicaid from January 1, 2011, through December 31, 2015, for the three-county region encompassing Hillsborough, Pasco, and Pinellas counties. Because the data use agreements in Florida prevented the sharing of OCW identifying information with AHCA, Mathematica obtained data on all enrollees in the geographic region and linked the data files to the OCW child welfare sample. However, not all Medicaid-eligible children in the OCW sample are necessarily enrolled in Medicaid in one of these counties, because they could have previously resided in another county. Therefore, it was not possible to identify and link all children, even those receiving Medicaid services, with their AHCA services information, given differences in the geography of the data samples.

II.2 summarizes the geographic and temporal differences in the Florida data provided by the four partner agencies.

II.2. Differences in the Florida data provided by partner agencies

Data agency	Sample geography	Sample time frame
OCW	Investigation county of intake was Hillsborough, Pasco, or Pinellas County	Full study period (January 2011–December 2015)
SAMH	Residence or receipt of services in Hillsborough, Pasco, or Pinellas counties	Full study period (January 2011–December 2015)
Eckerd	Receipt of CBC-purchased services in Hillsborough, Pasco, or Pinellas counties	Partial study period (August 2013–December 2015)
AHCA	Medicaid enrollment in Hillsborough, Pasco, or Pinellas counties	Full study period (January 2011–December 2015)

Additionally, because of specifications of the Medicaid data use agreement, Mathematica could only receive the last four digits of social security numbers (SSN) from AHCA. Coupled with the fact that OCW does not record Medicaid ID for parents, this limited the ability to link parents to Medicaid services. As a result, and as was the case with the Tennessee site, we focus the Florida analysis on the child, rather than the child and the parents.

B. Data processing and linking

With study data obtained from numerous site partners and each data partner sharing multiple files, the study team needed to process and link the data to consolidate information and create analytic files that matched data for individuals both within and across files in each site. The following sections describe the data processing and linking efforts for each of the study sites.

All the procedures outlined below were conducted with input from data experts at each agency, building on the documentation provided and addressing questions about the data as they came up in an iterative process.

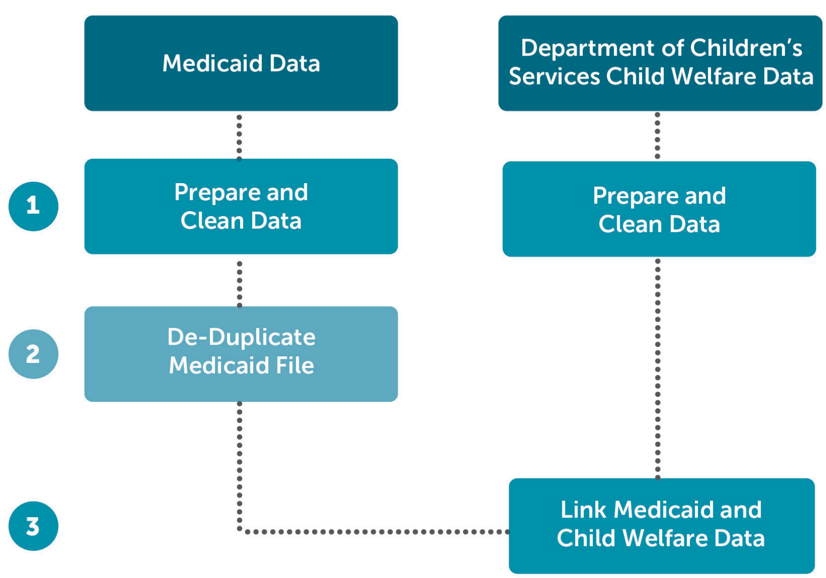
1. Tennessee

To create the analytical data sets, the first step was to carefully clean and prepare the data files for linking, which involved cleaning and standardizing linking variables. The next step involved de-duplication of available program IDs. After the data were prepared and de-duplicated, we could proceed with data linking. This process is illustrated for the Tennessee data files in Figure II.1 below.

The data sharing agreements allowed the child welfare agency (DCS) to directly share identifying information on children and parents in our study sample with the Medicaid agency (TennCare). TennCare used the available identifying information, specifically Medicaid ID, SSN, date of birth, and name, to identify corresponding Medicaid data files for those individuals. As a result, the Medicaid data TennCare shared with the Mathematica team were already limited to families identified by DCS, and the study team could use a deterministic matching approach to match children from the Tennessee child welfare data with their Medicaid data.

Deterministic matching requires observations to match exactly on the variables used for linking. We used Medicaid ID, SSN, and date of birth to link the data. Because unique identifiers (such as Medicaid ID, in this case) may contain transcription errors, we used date of birth and SSN to confirm the accuracy of the deterministic match (Kranker et al. 2014).

Figure II.1. Tennessee data processing and linking procedures



As shown in II.3, among cases where the child was taken into child welfare custody, the match rate was 82.0 percent. However, among all DCS children, which included custodial cases, non-custodial cases (cases with in-home services only, where the child was not taken into child welfare custody), and investigation only cases, we were able to link 160,920 to Medicaid data, resulting in a match rate of 49.2 percent. The lower overall match rate is likely due to children with CPS investigations and/or noncustodial cases, who are not necessarily eligible for Medicaid and do not have Medicaid IDs. The greater match rate among those in out-of-home child welfare custody, which was expected given children in custody are categorically eligible for Medicaid, informed our decision to limit the study sample to those who enter out-of-home custody.

II.3. Match rates for linkage to the Tennessee DCS sample

Agency	Match rate of DCS custodial cases (out-of-home placements)	Match rate for DCS non-custodial cases (in-home services only)	Match rate for DCS investigation-only cases	Overall match rate among all DCS children[a]
Medicaid	82.0%	65.9%	43.6%	49.2%
Number of children	**36,267**	**18,619**	**272,520**	**327,406**

Source: Tennessee DCS; TennCare.

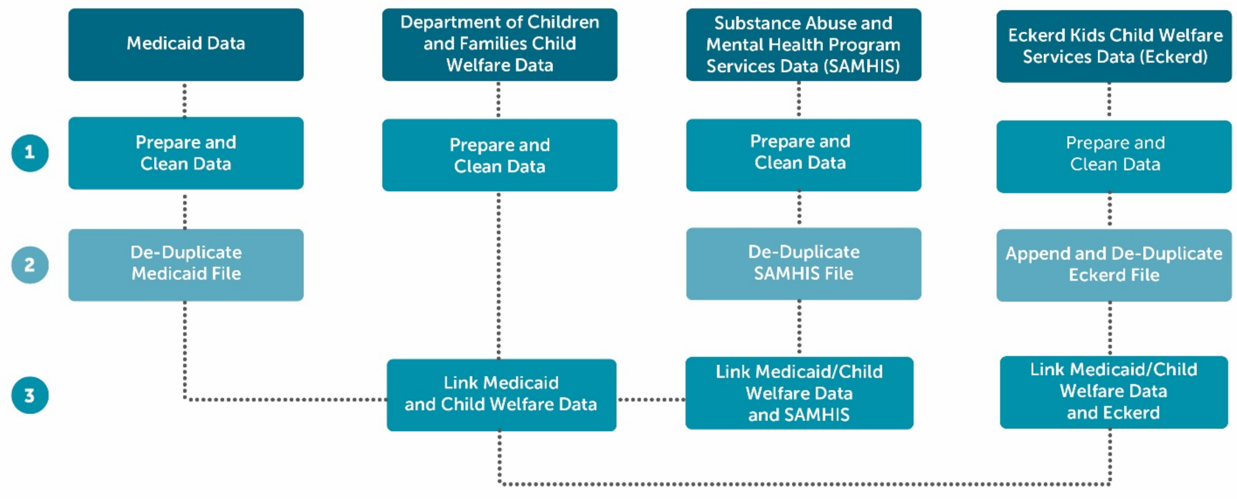
[a]Includes all children who were subject to an investigation.

2. Hillsborough, Pasco, and Pinellas counties, Florida

As mentioned earlier, for Hillsborough, Pasco, and Pinellas counties in Florida, we obtained data for the study from four separate agencies (OCW, AHCA, SAMH, and Eckerd). The data sharing agreements established between Mathematica and each of these agencies did not allow for any sharing of data among the agencies except between OCW and SAMH. Therefore, identifiers could not be shared across agencies to facilitate the identification of study participants among data files in each of the agencies. Also, due to differences in data sources and in the availability of key identifying information, we needed multiple data matching techniques to combine the data files within each site. Consequently, in Florida, the data management process, which included restricting the sample to the study's geographic scope, and the data linking process were more complex than in Tennessee.

To refine the data to restrict them to the study sample and to link all the data sources, we undertook a multistep approach that included the following. First, we limited the OCW child welfare data files to the geographic study area, using the county of intake from the CPS investigation. Second, we eliminated duplicate client information using program ID, name, and SSN; restructured the OCW, Medicaid, SAMH, and Eckerd data files; and linked the data within each organization. Third, we independently linked Medicaid, SAMH, and Eckerd child welfare services data to the OCW data using a combination of probabilistic and deterministic linking. Finally, once each set of data was linked with OCW, we consolidated all data into integrated relational data sets from which analytic files could be created. Each of these steps is depicted in Figure II.2 and further described in the following sections. Match results from the inter-agency linking process are presented in II.6 at the end of this section.

Figure II.2. Florida data processing and linking procedures



a. OCW to Medicaid data match

We used probabilistic matching to link children in child welfare custody in the OCW sample to Medicaid. Because only children placed in out-of-home care are categorically eligible for Medicaid, it was decided to limit the data-linking efforts between OCW and Medicaid to those children in child welfare custody, excluding those who only had CPS investigations. Due to high levels of missing values on key identifiers such as SSN and Medicaid ID in the OCW data, as well as incomplete identifiers in the Medicaid data, probabilistic matching presented the best opportunity for improving the match rate. As Paxton and colleagues (2014) explain, probabilistic matching links observations based on the likelihood that the variables used for matching uniquely identify an individual.

II.4 provides a list of variables we used for the probabilistic linking of Medicaid and OCW child welfare records.

II.4. Variables used for linking Florida Medicaid and OCW records

Type of identifier	Variable
Administrative	Social security number (last four digits)
	Medicaid ID
Name	Parent last name
	Soundex[a] of parent last name
Dates	Date of birth
Demographics	Gender

[a]Soundex is a coding system that indexes names based on the phonetic spelling. It is often used in data linking to suppress variations in spellings of last names (Gu et al. 2003).

In reviewing the results of the probabilistic match, we identified thresholds to distinguish high quality and unreliable matches. For matches that were below but near the threshold, we conducted a manual review process.

b. OCW to SAMH data match

To link SAMH substance abuse and mental health services data to children and their parents in the OCW child welfare sample, we took an iterative deterministic matching approach. Iterative deterministic matching is a common procedure in data linking that involves conducting multiple rounds of deterministic matching using successively weaker matching criteria (Kranker et al. 2013). The OCW and SAMH data shared several identifiers with low levels of missing data and high reliability that could be used for deterministic matching. Specifically, they contained full SSN, DOB, parent first and last name, and gender. Child first and last name was obtained through the previous match with Medicaid data; therefore, deterministic matching was appropriate for linking these data sets.

The deterministic matching process involved two steps: (1) matching records on full SSN and date of birth, excluding individuals with missing SSNs or an SSN that did not uniquely identify them (that is, two people sharing the same SSN), and (2) matching unmatched observations as well as those with missing and/or duplicate SSNs, using date of birth, first name, and last name. Observations with missing values on any of these three variables were excluded from this second deterministic match.

c. OCW to Eckerd data match

In addition to receiving child welfare data from the state child welfare agency, we also collected service data from Eckerd Kids, the lead Community Based Care (CBC) agency in Hillsborough, Pinellas, and Pasco counties. Specifically, Eckerd provided data on CBC-purchased services and costs for these services. To match children in the OCW sample with those receiving services from Eckerd, we used an iterative deterministic match similar to what was done to match SAMH and OCW data. However, before we could perform the deterministic match, extensive intra-agency matching of the multiple Eckerd data sets was required.

Eckerd provided two primary sets of data files for each county: one set contained information on specific child welfare services and cost and the second set consisted of weekly files containing identifying information, specifically SSN and date of birth, on children receiving Eckerd services. In order to link the detailed child welfare services from Eckerd with the OCW sample, it was necessary to link the SSN and date of birth from the weekly files to the services files. II.5 outlines the process used to construct a child-level Eckerd data file.

II.5. Intra-agency deterministic matching procedure for Eckerd Kids

Matching step	Matching variable
Appending, standardization, and de-duplication of weekly files	SSN, Date of Birth, Child First Name, Child Last Name, Parent First Name, Parent Last Name
Manual data cleaning, appending, standardization, and de-duplication of services files	Child First Name, Child Last Name, Parent First Name, Parent Last Name
Linking appended weekly file with appended services file for children with unique first and last names	Child First Name, Child Last Name
Linking unmerged records, and/or children with non-unique first and last names by child and parent name	Child First Name, Child Last Name, Parent First Name, Parent Last Name

Specifically, we appended all weekly data files for all three counties together and de-duplicated using child SSN, date of birth, and name to create a single, unique, child-level universe of Eckerd children. Similarly, data on services from each county were appended to create a single data set of all Eckerd services. Because of differences in how the child's name was stored between the weekly files and the services file, both data files underwent extensive data cleaning to standardize name fields prior to linking them using a combination of child name and parent name.

With the intra-agency match complete among the Eckerd data files, the next step was to link Eckerd's services file to the OCW sample using SSN, child name, and date of birth. As mentioned earlier, we matched the Eckerd sample to OCW using the same iterative deterministic matching process used to match the SAMH records to the OCW sample.

d. Data linking across all Florida agency data

The results of each inter-agency data linkage to the OCW sample are summarized in II.6.

II.6. Match rates for linkage to the OCW sample

Agency	Match rate for OCW children with out-of-home placements	Match rate for OCW children with in-home services only	Match rate for OCW children with investigation only	Overall match rate among all OCW children[a]
Medicaid	89.1%	76.3%	1.3%	20.7%
SAMH	22.7%	17.2%	10.3%	12.8%
Eckerd	12.9%	1.5%	0.0%	2.4%
Number of children	**20,231**	**6,212**	**89,206**	**115,649**

Source: Florida OCW; Florida AHCA, Florida Eckerd; Florida SAMH.

Note: Eckerd merge rates are reported for children with detailed child welfare services information.

[a]Includes all children who were subject to an investigation.

In total, we matched 89.1 percent of OCW children with an out-of-home placement with Medicaid data. We were also able to match 76.3 percent of in-home services-only children with Medicaid data. Considering that not all children in the OCW sample may be eligible for Medicaid (such as those receiving only in-home services or those who were only subject to an investigation and do not qualify for other reasons), as well as geographic differences in the Medicaid and OCW data, these match rates are consistent with expectations.[1]

Although most children during child welfare custody receive mental health and substance abuse services through Medicaid, some children may have also received services from SAHM. Overall, 22.7 percent of children with a OCW out-of-home placement were matched with SAMH data. Although not the focus of the study scope, we were able to match roughly 30 percent of parents. Given that SAMH data only includes information on non-Medicaid mental health and substance abuse services, and only a subset of children and parents involved with the child welfare system will receive treatment for mental health or substance abuse issues, these merge

[1] Medicaid data contain information on individuals enrolled in Medicaid in the study region. OCW data contain information on individuals who had an investigation, regardless of residency status, in the study region.

rates are within reasonable expectations.[2] Florida partners stated that SAMH provides services to children in foster care when Medicaid determines that services are "not medically necessary" but the state thinks otherwise or if Medicaid service availability is an issue.

Finally, 12.9 percent of children in OCW custody with an out-of-home placement were matched with the Eckerd data. Some reasons for the low match rate include the limited time frame within the study window for which Eckerd data were available, jurisdictional differences in how children are associated with site counties by Eckerd and OCW, and limitations in associating SSN and DOB information with Eckerd services through the intra-agency merge.

C. Analytic file construction

After data linking, we used the linked data to create additional variables, and restructured those data into a set of clean analytic files. Distinct analytic files were created for the two study sites (Tennessee and the three Florida counties). Analysis was conducted separately for each site, given differences in their respective programs and policies, variable definitions, and data availability.

The differences in the sites and the variety of planned analyses necessitated a flexible structure to the analytic data sets. For each site, rather than a single flat data set, we instead created a group of data sets, similar to a relational database, which included a child-level, parent-level, investigations-level, episode-level, placement-level, and services-level data set. Each data set is linkable to the child-level data set using a unique child ID. Additionally, all child welfare and Medicaid services, as well as child welfare placements, can be linked to the episode-level data set using a unique episode ID.

The creation of these relational analytic data sets made it possible to easily transform the data into the requisite format for each analysis. In particular, to create the analysis files for the descriptive and latent class analyses, information on child welfare services, placements, episodes, investigations, and assessments, as well as Medicaid services, were rolled up to the child level. Additionally, in Florida, information on substance use and mental health services were aggregated to the child level. For the predictive analysis, the data were transformed into a child episode-level data set, using information on the start and end date for each episode within each child's data. This allowed for the creation of analytic files with two distinct time periods, a lookback and a prediction time period, which were necessary for predictive analysis.

[2] The SAMHIS files contain information on services and assessments received for substance abuse and mental health for both children and adults who were served or who resided in one of the study counties. The OCW data were limited to children with an investigation in one of the study counties during the study window, January 1, 2011–December 31, 2015.

This page has been left blank for double-sided copying.

III. DESCRIPTION OF THE STUDY SAMPLE

A. Introduction

This chapter provides a description of the study samples for both study sites: the state of Tennessee (hereafter referred to as the Tennessee sample) and Hillsborough, Pinellas, and Pasco counties, Florida (hereafter referred to as the Florida sample). For both sites, we limited the study sample to those children who entered child welfare out-of-home custody within the study time frame (that is, the children's out-of-home custody start dates are within the study time frame). The sample was not restricted to first-time entrants into out-of-home custody, but did exclude those in custody due to juvenile justice involvement.

We used children who entered out-of-home custody from the child welfare data as the primary factor for inclusion in the study sample. We did not limit the study sample to only those children with available Medicaid, Eckerd, or SAMH services data. After our matching procedures, if we could not identify the children with out-of-home custody episodes in the datasets for these other services, we assumed they did not receive those services.

The sample time frame was also limited based on when data were available for all data sources for each site. In particular, the time frame for the Florida study site was limited to the shortened time period in which Eckerd services data were available. Although Eckerd services were only available for a limited period of time within the study window, the data are an important component for our measurement of service utilization for children in child welfare. Without these data, our assessment of child welfare service use would be constrained to only custody episodes and foster care placements. The objective of the study is to better understand the broader use of services, including other child welfare services, which is only available from the Eckerd data for the Florida sample. Therefore, we decided to use the limited time frame in which we had complete data for all services in Florida. Given differences in data availability for each study site, the time frame used to identify the sample differs for each of the study sites, as noted below:

- Tennessee sample time frame: July 1, 2011–December 31, 2015
- Florida sample time frame: September 1, 2013–December 31, 2015

The following sections of this chapter present a description of key characteristics and child welfare experiences and outcomes of the study samples for Tennessee and Florida. The full set of results can be found in Appendix A.

B. Sample overview

1. Tennessee sample

The Tennessee study sample consists of 21,672 children who entered child welfare out-of-home custody between July 1, 2011, and December 31, 2015. The children in the study sample are associated with DCS regions across the state. The highest proportion (9.9 percent) come from the Special Investigations Unit (SIU), which conducts investigations of allegations of child maltreatment that occur while the child is in DCS custody; the next highest proportions come from the Shelby (9.2 percent), Mid-Cumberland (9.1 percent), Upper Cumberland (8.7 percent), and Smokey Mountain regions (8.7 percent). III.1, below, depicts the distribution of the study sample across Tennessee DCS regions.

III.1. Tennessee sample by DCS region

	Number of children	Percentage of children
DCS regions		
Davidson	1,059	4.9
East Tennessee	1,400	6.5
Knox	1,716	7.9
Mid-Cumberland	1,970	9.1
Northeast	1,545	7.1
Northwest	894	4.1
Shelby	1,997	9.2
Smoky Mountain	1,880	8.7
South Central	1,055	4.9
Southwest	809	3.7
Tennessee Valley	1,595	7.4
Upper Cumberland	1,880	8.7
Child Abuse Hotline	4	0.0
DCS central office	6	0.0
SIU	2,135	9.9
Missing	1,727	8.0
Number of children	**21,672**	

Source: Tennessee DCS.

Note: Children were allocated to region based on the region associated with the last-closed investigation. A map of Tennessee DCS regions can be found via the following link: https://www.tn.gov/assets/entities/dcs/attachments/DCS_Regional_Map_June_2016.pdf.

2. Florida sample

The Florida sample consists of 6,695 children who entered out-of-home custody between September 1, 2013, and December 31, 2015. As shown in III.2, below, about half (51.5 percent) of the study sample is from Hillsborough county, with the remaining from Pinellas (28.2 percent) and Pasco counties (20.3 percent).

III.2. Florida sample by county

	Number of children	Percentage of children
Counties		
Hillsborough	3,451	51.5
Pasco	1,358	20.3
Pinellas	1,886	28.2
Number of children	**6,695**	

Source: Florida OCW.

Note: Children were allocated to county based on the county associated with the last-closed investigation.

C. Demographic characteristics

The demographic characteristics for the study samples in Tennessee and Florida are depicted in III.3 below. For the Tennessee sample, 16.1 percent of children are younger than 1 year old and there are almost equal percentages of children among the age groups of children ages 1 to less than 6 (28.1 percent), ages 6 to less than 13 (27.5 percent), and ages 13 to less than 18 (28.2 percent). The Florida sample has more variability across the age groups, with the highest percentage (34.8 percent) among children ages 1 to less than 6, followed by the next highest percentage (28.9 percent) among children ages 6 to less than 13. Both study samples have fairly equal proportion of males and females. In regard to race and ethnicity, in both the Tennessee and Florida samples, the largest percentage of children are identified as white (75.8 percent and 69.1 percent, respectively). However, Florida has a higher percentage of children identified as other racial and ethnic categories, with black (36.9 percent) and Hispanic (13.8 percent) the highest among them.

III.3. Sample demographics

	Tennessee		Florida	
	Number of children	Percentage of children	Number of children	Percentage of children
Age at time of first custody/service during lifetime				
Less than 1	3,483	16.1	1,303	19.5
1 to less than 6 years old	6,084	28.1	2,333	34.8
6 to less than 13 years old	5,965	27.5	1,932	28.9
13 to less than 18 years old	6,112	28.2	1,038	15.5
18 to less than 24 years old[a]	6	0.0	0	0.0
Missing	22	0.1	89	1.3
Gender				
Male	10,990	50.7	3,418	51.1
Female	10,673	49.2	3,277	48.9
Unknown	9	0.0	0	0.0
Race/ethnicity				
White	16,434	75.8	4,625	69.1
Black	5,423	25.0	2,468	36.9
Hispanic/Latino	1,066	4.9	923	13.8
Asian	51	0.2	38	0.6
American Indian/Alaskan Native	76	0.4	18	0.3
Native Hawaiian/Pacific Islander	39	0.2	2	0.0
Multiracial when one race is unknown[b]	133	0.6	–	–
Missing	693	3.2	33	0.5
Number of children	**21,672**		**6,695**	

Source: Tennessee DCS; Florida OCW.

Note: For the Tennessee sample, age was calculated at time of first custodial episode that started within the study window. For the Florida sample, age was calculated at first child welfare out-of-home placement within episodes that started in the study window.
Race and ethnicity values are not mutually exclusive.

[a]In Florida, age information was set to missing for all children with reported ages of 23 and older. In Tennessee, age information was set to missing for all children with reported ages of 24 and older. These cutoffs are consistent with extended foster-care age restrictions in each state.

[b]"Multiracial when one race is unknown" is a SACWIS race value that is selected for persons suspected or known to be more than one race, but for whom only one race has been identified. This category is reported by Tennessee only.

D. Child welfare experiences and outcomes

1. Child welfare history, episodes, and placements

Almost half (44.7 percent) of the children in the Tennessee sample and just over half (52.3 percent) of the children in the Florida sample had prior child protection investigations, meaning investigations prior to any that may be associated with the custody episode that qualified them for the study sample. Also, 9.9 percent of children in the Tennessee sample had prior child welfare out-of-home custody episodes before the study time frame. When looking at the number of child welfare episodes over the life of the child, including prior to and within the study window, most (85.1 percent) children had one prior episode. In the Florida sample, 14.1 percent of children had prior child welfare out-of-home custody episodes. When looking at the child's history of child welfare episodes over their lifetime, most (75.1 percent) had one prior episode. On average, children in the Tennessee and Florida samples experienced 3.4 and 4.2 placement moves across all episodes, respectively. Child welfare history, number of episodes, and number of placements among the Tennessee and Florida samples are described in III.4, below.

III.4. Child welfare history, episodes, and placements

	Tennessee		Florida	
	Number of children	Percentage of children	Number of children	Percentage of children
Prior investigations	9,690	44.7	3,502	52.3
Prior child welfare custodial episode	2,143	9.9	944	14.1
Number of child welfare episodes over the life of the child				
One episode	18,436	85.1	5,031	75.1
Two episodes	2,697	12.4	1,261	18.8
Three episodes	428	2.0	305	4.6
Four or more episodes	111	0.5	98	1.5
Number of placement moves across all episodes				
One move	4,923	22.7	1,193	17.8
Two moves	5,987	27.6	1,849	27.6
Three moves	3,892	18.0	1,319	19.7
Four moves	2,387	11.0	756	11.3
Five moves	1,436	6.6	430	6.4
Six moves	833	3.8	291	4.3
Seven or more moves	2,202	10.2	857	12.8
Missing	12	0.1	0	0.0
Number of children	**21,672**		**6,695**	

Source: Tennessee DCS; Florida OCW.

Note: Prior episodes and prior investigations include episodes or investigations that started prior to the study window. The count of prior investigations excludes any investigations that are associated with an episode that began during the study window. The number of episodes and placements includes ones that are right-censored, meaning they are ongoing at the end of the study time period.

In Tennessee, an episode is defined as a period of time in out-of-home care, but may also include trial home visits before child welfare custody ends. In Florida, an episode is defined by any period of time in in-home or out-of-home care. Florida estimates reported in the include episodes composed entirely of in-home placements.

In addition to the number of placements, the type of placement is also important. We specifically looked at the extent to which children are placed in family foster care, meaning family foster care placements such as relative or non-relative foster care, and the extent to which children are in group home, residential treatment, or other instiutational settings. On average, children in the Tennessee sample are in family foster care placements 78.6 percent of the time they are in out-of-home placements, and they are in group home, residential treatment or other instiutational settings 8.1 percent of the time they are in out-of-home placements. Children in the Florida sample are in family foster care placements an average of 68.7 percent of the time they are in out-of-home placements, and they are in group, institutional, or residential care an average of 5.8 percent of the time they are in out-of home placements. Please note that due to other types of placements tracked while children are in custody, including temporarily being placed in hospitals, runaway, or juvenile detention, the percent of time in family foster care and the percent of time children may be in group, instutional, or residential care will not add up to 100 percent.

2. Removal reason

Tennessee DCS provided data regarding the reason for removal and placement into out-of-home custody; however, similar data were unavailable for the Florida sample. Among those in the Tennessee sample, the highest percentage of children had parental drug abuse (38.4 percent) as the reason for removal, with neglect (37.9 percent) close behind as the next highest reason for removal. It is important to note that children can be associated with more than one reason for removal. Additional findings regarding removal reason are presented in III.5, below.

III.5. Tennessee Sample: Reason for removal

	Number of children	Percentage of children
Reasons for removal:		
Drug abuse (parent)	8,323	38.4
Neglect (alleged/reported)	8,205	37.9
Child's behavioral problem[a]	2,902	13.4
Physical abuse (alleged/reported)	2,441	11.3
Abandonment	2,360	10.9
Incarceration of parent(s)	2,112	9.7
Inadequate Housing	1,955	9.0
Caretaker inability to cope due to illness or other reasons	1,888	8.7
Sexual abuse (alleged/reported)	1,141	5.3
Truancy	874	4.0
Alcohol abuse (parent)	589	2.7
Drug abuse (child)	489	2.3
Relinquishment	316	1.5
Death of parent(s)	230	1.1
Child's disability	111	0.5
Alcohol abuse (child)	63	0.3
Neonatal abstinence syndrome (NAS) prosecution	2	0.0
Number of children	**21,672**	

Source: Tennessee DCS.
Note: The share reported for each reason for removal is the share of children who were placed in at least one custody episode for that reason. The case manager is able to check multiple reasons for removal.
[a]"Child's behavioral problem" is not an allegation type, and refers to situations where the child comes into custody through the court, and has behavioral issues that the parents cannot address and/or control (e.g., aggressive

behaviors, chronic runaway behaviors, oppositional/defiance towards parents and authority figures). Case managers are able to check multiple reasons for removal, so they may check this box in addition to the allegation that resulted in the child's removal, if significant behavioral problems exist for the child/youth and the parents are unable to respond appropriately.

3. Assessments

Information regarding several assessments was also available for each study sample. Specifically, child welfare assessments of Child and Adolescent Needs and Strengths (CANS), Family Advocacy and Support Tool (FAST), Ansell-Casey Life Skills, and Youth Level of Service (YLS) were available from Tennessee DCS. Among those in the Tennessee study sample, 63.7 percent had CANS scores. The CANS assessment evaluates a child's needs and strengths and is used for case decision-making and planning purposes. Of those with CANS score, the majority (78.9 percent) of the sample had the lowest level (Level 1) score, meaning fewer needs were identified. Also, about half (49.8 percent) of the Tennessee study sample had FAST scores, which is an assessment that evaluates the needs of families. Of those with a FAST score, most (70.5 percent) of the sample had a low score, indicating lower needs. 21.4 percent of the Tennessee study sample had the Ansell-Casey Life Skills assessment, however it is important to note that not everyone would be appropriate for this assessment given this is a tool to assess the behaviors and competencies of youth ages 14 to 21. The average score on Ansell-Casey Life Skills assessment was 36, indicating children typically had below average life skill development. Only 1.8 percent of children in the Tennessee sample had YLS scores, however as with the previous type of assessment, not all children would be age-appropriate for the YLS, given it is an assessment tool to assess the risks and needs of adolescents; children on average had a YLS score of 12.1. The YLS ranges from 0 (low risk) to 42 (high risk), with 12.1 representing moderate risk.

Florida OCW provided information about the child welfare risk assessment, which is conducted as part of the investigation. Among the Florida sample, 47.2 percent had OCW investigation risk scores. Among those with risk scores, over half (54 percent) of the sample had a high score, indicating higher levels of need. Several assessments used by Florida SAMH were also provided, including the Functional Assessment Rating Scale (FARS), Children's Functional Assessment Rating Scale (CFARS), and American Society of Additction Medicine (ASAM) assessments; however, these scores were only available for the small percentage of the study sample who were also receiving services from SAMH and are not reported here.

4. Legal status at end of Study Window

In regard to child welfare permanency outcomes, 70.2 percent of the Tennessee sample exited custody within the study window. Although only 47.3 percent of the Florida sample exited custody within the study window, this was expected, given a shorter study window of only 28 months of data availability. Given there are more cases in the Florida sample that are right-censored (meaning still in custody at the end of the study time period), we have less-complete information for these cases about the full array of services received. However, our conceptualization of superutilization is not limited to only those with complete custody episodes and our measurement approach attempts to adjust for the amount of time in which children were exposed to the study window, using rate measures, as discussed in Chapter V.

For both sites, the highest proportion among those who exited custody among the study samples experienced reunification: 47.6 percent of children in the Tennessee sample and 68.4 percent in the Florida sample. In regard to adoption, 17.2 percent of those who exited custody in the Tennessee sample and 10.2 percent of those who exited custody in the Florida sample achieved adoption. However, given the shorter study time frame for Florida, it is expected that fewer cases would experience legal permanency that typically have longer durations, such as adoption. III.6, below, presents information about permanency types as well as length of stay in custody until permanency exit.

III.6. Permanency outcomes by end of study window

			Length of stay (days) until permanency exit			
	Number of children	Percentage of children	Mean	Median	Minimum	Maximum
Tennessee						
Exited custody	15,206	70.2	347.4	291.0	1.0	1,540.0
Remained in custody	6,466	29.8	–	–	–	–
Status of those children who exited custody (n = 15,206):						
Reunification	7,232	47.6	272.1	237.0	1.0	1,445.0
Relative/kinship placement	3,062	20.1	178.4	116.5	1.0	1,247.0
Adoption	2,612	17.2	687.5	657.0	53.0	1,540.0
Emancipation	1,252	8.2	403.0	324.0	3.0	1,532.0
Guardianship	912	6.0	486.8	440.0	6.0	1,418.0
Death	36	0.2	183.7	96.0	1.0	1,010.0
Other[a]	100	0.7	178.5	50.0	1.0	1,327.0
Number of children						**21,672**
Florida						
Exited custody	3,170	47.3	251.9	233.0	2.0	829.0
Remained in custody	3,472	51.9	–	–	–	–
Missing	53	0.8	–	–	–	–
Status of those children who exited custody (n = 3,170)						
Reunification	2,167	68.4	198.3	181.0	2.0	826.0
Guardianship	524	16.5	346.0	328.0	6.0	829.0
Adoption	322	10.2	468.4	503.5	28.0	816.0
Aged out or emancipated	106	3.3	255.0	223.0	12.0	776.0
Death	3	0.1	272.0	250.0	8.0	558.0
Other[a]	48	1.5	183.9	91.5	3.0	556.0
Number of children						**6,695**

Source: Tennessee DCS; Florida OCW.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit. Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

[a]Other includes runaways and transfers to another agency.

This page has been left blank for double-sided copying.

IV. SERVICE USE AMONG STUDY SAMPLE

A. Introduction

This chapter describes the use of child welfare, Medicaid, and other services among those in child welfare custody for the Tennessee and Florida samples. Child welfare custody episodes and placements are inclusive of all known instances over the life of the child through the end of the study window. However, all other services, specifically child welfare services, Medicaid, and substance abuse and mental health services, were measured during the study time frame using available services data for those in the study sample, including both right- and left-censored services that respectively began before or continued after the study time frame. All results in this chapter are based on descriptive analysis using SAS. While the following sections present key findings, the full set of results can be found in Appendix A.

B. Child welfare services

Information about services provided by child welfare agencies is captured differently in the data for each study site. Tennessee DCS collected a rich set of services information as part of their data system, which allowed us to identify child welfare services for 84.1 percent of the study sample in that state. For others in the study sample, we assume they did not receive child welfare services aside from placements and case management. In Florida, which is a privatized child welfare system and uses Community Based Care (CBC) providers, we obtained child welfare services (referred to as CBC-purchased services) data from Eckerd, the contracted CBC service provider. We linked Eckerd data with OCW data on children in the study sample to identify their child welfare CBC-purchased services. We identified child welfare CBC-purchased services for 19.8 percent of the Florida sample. Although this percentage is lower than for Tennessee, it is consistent with estimates provided by Eckerd, which noted that few services are provided beyond what is covered by Medicaid. Findings regarding services received among the study samples are depicted in IV.1, below.

Given that the study samples for both sites are focused on those with out-of-home custody episodes, most services were identified as custodial services, meaning those services that started during an out-of-home custody. Specifically, among children receiving child welfare services, most are custodial services, with 94.9 percent of those receiving child welfare services in the Tennessee sample and 89.3 percent of those receiving child welfare CBC-purchased services in the Florida sample received custodial services. However, some of those in the study sample also had in-home services: 28.9 percent among children receiving child welfare services in the Tennessee sample and 16.9 percent among children receiving CBC-purchased child welfare services in the Florida sample also had in-home services during the study window.

IV.1. Receipt of child welfare services

	Tennessee		Florida	
	Number of children	Percentage of children	Number of children	Percentage of children
Children receiving child welfare services	18,220	84.1	1,325	19.8
Among children receiving child welfare services:				
Children receiving custodial services	17,296	94.9	1,183	89.3
Children receiving noncustodial services	5,269	28.9	224	16.9
Number of children	**21,672**		**6,695**	

Source: Tennessee DCS; Florida OCW; Florida Eckerd.

Note: Child welfare services for Florida are the CBC-purchased services provided by Eckerd. Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

When assessing the number of services for each child, the average number of services per child in the Tennessee sample was six services and the average number of services per child in the Florida sample was two services.

Given the richness of the Tennessee child welfare services data, we were able to assess receipt of numerous types of services among the Tennessee study sample. There were over 300 types of services, which we consolidated into fewer categories with input from DCS. The types of child welfare services and the number and percentage of children receiving those services are identified in IV.2, below. Among those receiving child welfare services, the highest percentage (71.8 percent) received clothing assistance. Over a quarter (29.3 percent) received substance abuse testing and treatment services, which was predominately testing services. The next most common service categories included other services (27.9 percent), assessments (20.2 percent), family or parenting support services (20.0 percent), therapy or counseling (18.6 percent), and legal services (18.5 percent).

IV.2. Tennessee sample: Types of services received

	Number of children	Percentage of children
Types of services received among children receiving child welfare services (n = 18,220)		
Clothing assistance	13,085	71.8
Substance abuse testing and treatment[a]	5,337	29.3
Assessment	3,677	20.2
Family/parenting support	3,648	20.0
Therapy/counseling	3,389	18.6
Legal	3,370	18.5
Transit assistance	3,044	16.7
Documentation[b]	2,892	15.9
Supervised visitation	2,872	15.8
Housing assistance	1,413	7.8
Caregiver/parenting	1,304	7.2
Child care assistance	1,136	6.2
Education support	608	3.3
Respite	486	2.7
Language/interpretation	288	1.6
Extension of foster care	287	1.6
Independent living support	242	1.3
Youth enrichment/support	196	1.1
Drivers education support	88	0.5
Employment/training	71	0.4
Mentoring	54	0.3
Health	44	0.2
Burial assistance for child	25	0.1
Other[c]	5,082	27.9
Number of children	**21,672**	

Source: Tennessee DCS.

[a]Substance abuse services consist primarily of testing services.

[b]Documentation services include services related to birth certificates, certified copying of legal documents, medical records, photo ids, transcript services, digital video copies, and videographer services.

[c]Other services include other support services, paternity testing, surveillance/monitoring, and temporary breaks.

For the Florida sample, we followed a similar process and worked with Eckerd to reduce the number of services into categories. The number and percentage of children receiving each type of service are depicted in IV.3, below. Among those who received child welfare CBC-purchased services, assessments were received by the highest percentage (20.9 percent). The next most common services were other services (19.7 percent), documentation services (17.3 percent), putative father registry (15.1 percent), family and caregiver support services (13.97 percent), and therapy and counseling (12.7 percent).

IV.3. Florida sample: Types of CBC-purchased services received

	Number of children	Percentage of children
Types of services received among children receiving child welfare CBC-purchased services (n = 1,325)		
Assessment	277	20.9
Documentation services	229	17.3
Putative father registry	200	15.1
Family/caregiver support services	184	13.9
Therapy/counseling	168	12.7
Child care assistance	101	7.6
Housing assistance	92	6.9
Transportation assistance	79	6.0
Health services	72	5.4
Youth support services	49	3.7
Education supports	48	3.6
Caregiver/parenting education	35	2.6
Substance abuse testing/treatment	30	2.3
Supervised visitation	12	0.9
Case management	2	0.2
Language/interpretation services	2	0.2
Mentoring	3	0.2
Respite	1	0.1
Legal services	0	0.0
Other[a]	261	19.7
Number of children	**6,695**	

Source: Florida OCW; Florida Eckerd.

[a]Other services include autism spectrum, behavioral assistance, Community Kids, IV-E waiver stipend, nonspecific to any area, other, paternity testing, reimbursement, Restorative Justice Program, shipping of luggage, state institutional claim, and uninsured children.

C. Medicaid services

The majority of children in the child welfare samples also received Medicaid services in the study window. Specifically, 85.6 percent of the Tennessee sample and 91.5 percent of the Florida sample received Medicaid services. Among the types of Medicaid services, the highest percentage (85.4 percent in Tennessee and 90.8 percent in Florida) of the study samples received outpatient services. Emergency services (that is, services provided in emergency departments) were received by 70.1 percent of the sample in Tennessee and 64.5 percent of the sample in Florida. The same percentage (17.0 percent) of the study sample in both sites received Medicaid inpatient physical and behavioral health (i.e., psychiatric) services. Findings regarding Medicaid service use among the study samples are depicted in IV.4, below.

IV.4. Types of Medicaid services for those receiving services

	Number of children	Percentage of children	Number of services			
			Mean	Median	Minimum	Maximum
Tennessee:						
Medicaid services	18,554	85.6				
Inpatient services	3,678	17.0	1.8	1.0	1.0	29.0
Physical health	2,483	67.5	1.5	1.0	1.0	27.0
Behavioral health	1,450	39.4	2.1	1.0	1.0	22.0
Outpatient services	18,504	85.4	37.1	24.0	1.0	454.0
Physical health	18,442	99.7	16.4	13.0	1.0	177.0
Behavioral health	11,867	64.1	32.4	18.0	1.0	408.0
Emergency services	15,186	70.1	4.8	3.0	1.0	103.0
Physical health	15,094	99.4	4.6	3.0	1.0	96.0
Behavioral health	1,596	10.5	1.7	1.0	1.0	21.0
Number of children	**21,672**					
Florida:						
Medicaid services	6,126	91.5				
Inpatient services	1,137	17.0	2.8	1.0	1.0	78.0
Physical health	853	75.0	1.8	1.0	1.0	27.0
Behavioral health	341	30.0	4.9	2.0	1.0	78.0
Outpatient services	6,082	90.8	24.8	16.0	1.0	688.0
Physical health	5,987	98.4	11.5	9.0	1.0	131.0
Behavioral health	3,355	55.2	24.4	14.0	1.0	658.0
Emergency services	4,316	64.5	3.4	2.0	1.0	70.0
Physical health	4,306	99.8	3.3	2.0	1.0	61.0
Behavioral health	199	4.6	1.7	1.0	1.0	9.0
Number of children	**6,695**					

Source: Tennessee DCS; TennCare; Florida OCW; Florida AHCA.
Note: Distributions are calculated among children receiving services.

D. Other substance abuse and mental health services

For the Florida study sample, we received services information about additional substance abuse and mental health services not covered by Medicaid that were provided by Florida SAMH. We found 15.8 percent of the child welfare sample in Florida received SAMH services, with 4.9 percent of the sample receiving substance abuse services and 14.0 percent receiving mental health services. Those who received SAMH services received an average of 2.4 services within the study window. Findings regarding these substance abuse and mental health services are depicted in IV.5, below.

IV.5. Florida sample: Substance abuse and mental health services for those receiving services

	Number of children	Percentage of children	Number of services			
			Mean	Median	Minimum	Maximum
Any SAMH service per child	1,059	15.8	2.4	1.0	1.0	55.0
Substance abuse services[a]	330	4.9	2.6	1.0	1.0	47.0
24-hour services	17	5.2	1.4	1.0	1.0	3.0
Acute services	52	15.8	1.2	1.0	1.0	3.0
Outpatient services	314	95.2	2.5	1.0	1.0	46.0
Mental health services[a]	939	14.0	1.8	1.0	1.0	17.0
24-hour services	18	1.9	1.2	1.0	1.0	3.0
Acute services	177	18.8	2.0	1.0	1.0	10.0
Outpatient services	896	95.4	1.5	1.0	1.0	7.0
Number of children	**6,695**					

Source: Florida OCW; Florida SAMH.

Notes: Distributions are calculated across those receiving services.

Services are denominated in treatment episodes. Multiple treatment episodes can occur at the same time. Counts of services by subtype of care are counts of treatment episodes that included each subtype of care.

[a]24-hour services include residential care levels 1–4, room & board with supervision levels 1–3, and short-term residential treatment. Acute care includes crisis stabilization, crisis support/emergency, inpatient, and substance abuse detoxification. Outpatient includes all other services, for example, assessment, intervention, outreach, prevention, methadone maintenance, FACT team, etc.

V. MEASUREMENT OF SUPERUTILIZATION OF SERVICES

A. Introduction

After identifying the characteristics and service use of the study samples, we turn to a key objective of this study, which is to better understand the characteristics of children who receive high levels of services available through the child welfare system (that is, those who experience superutilization). We hope this information can provide program staff and policymakers with actionable insights into the factors that may contribute to overuse of services and help the child welfare system to develop more timely, targeted, and effective services for children with specific service needs.

To this end, a critical first step is defining the concept of superutilization and operationalizing that concept into observed measurable components. Although we provided our general conceptualization of superutilization in Chapter I, in this chapter, we elaborate on the considerations the team made in selecting potential indicators of superutilization for use in the analysis and provide our operational measures of the concept. We conclude with a summary of superutilization measures we used for this study and identify those among the study sample that experienced superutilization.

B. Conceptualizing superutilization

As discussed in Chapter I, we define superutilization as a level of service utilization or receipt that can be characterized as high based on a threshold. Building on this general definition, we also regard superutilization as a multidimensional concept that encompasses intensity, frequency, duration, and cost of service use. In this respect, the experience of superutilization can be specific to a given dimension. Before discussing our considerations for determining where the threshold values should be for our superutilization measures, we first elaborate on the criteria used to select variables to measure superutilization.

1. Criteria for measures used to define superutilization

As part of the measurement process, we examined data for Tennessee and Florida to identify and construct specific measures that mapped to the four dimensions of superutilization referenced above. As noted in Chapter II, information on child welfare episodes, placements, and services, Medicaid services, and, for Florida, substance abuse and mental health services not paid for by Medicaid, were rolled up to the child level in the analysis files. This process produced extensive data for each child on a variety of measures. However, to maximize alignment between the constructed measures and the core research questions, we further adjusted the data and refined the final list of measures based on how well potential measures satisfied the following criteria:

- **Relevance.** How well does a measure relate to a given dimension of superutilization? This criterion focuses on the construct validity of a proposed measure. Specifically, this addresses whether the selected measures capture what they are intended to measure. Based on discussions among the project team, which included subject matter experts, we selected measures that conceptually mapped most closely to the dimensions of interest.

- **Availability.** Are measures or relevant information to construct measures available in the data files that we received from our study partners? We used this criterion to the extent possible to guide our inclusion of measures for analysis. As noted in Chapters I and II, the cost data for Tennessee and Florida were incomplete, which limited our ability to use these data to measure superutilization. Despite limitations, however, we included cost data for the child welfare services and placements for which there was coverage.
- **Accuracy.** How good are the data at capturing the desired information? The accuracy of the data was also an important factor in the decision to include and map measures of superutilization. During the review process, we assessed the accuracy of the variables by checking for consistency of dates of services, placements, and other key indicators. In selecting measures that map to different dimensions of superutilization, we chose indicators with minimal counts of missing values and inconsistencies. In addition, the team formulated a set of rules for consistent treatment of missing values in the construction of variables that were mapped to different domains. Details on the procedures used to construct the variables are provided in Appendix B. Maximizing the accuracy of the data was also a key consideration in how best to use the available Medicaid data. One key issue when constructing Medicaid measures was to account for the periods in which a child was actually eligible to receive Medicaid services. Because all children in out-of-home custody are eligible for Medicaid, we restricted the study sample to include only children who began custody episodes with out-of-home placements during the study window.[3] This ensured that Medicaid eligibility was accurately measured for the study samples.
- **Ability to harmonize.** How easily can we can combine the data from different sources so that they can be consistently measured at the child level and used for subsequent analysis? As noted in Chapter II, for this study, we used administrative data from a variety of sources, including state child welfare agencies, a contracted private child welfare services provider, state Medicaid, and state substance abuse and mental health services. For Tennessee, the data were provided by DCS and TennCare. For both sources, the period covered by the data was consistent, which enabled us to examine the full five-year time period covered by the data (2011 to 2015). For this study, Eckerd was the primary source for the child welfare services and associated cost data in Florida; therefore we decided to restrict the Florida sample window to be consistent with the roughly two-year window for which Eckerd data were available. Although the decision resulted in a reduction in potential sample size for the Florida analysis, we made this restriction in order to harmonize the coverage of all Florida data and to prevent any confounding between observed patterns in the data with inconsistencies in the coverage period.

2. Measures of superutilization

Based on the considerations mentioned above, we identified a total of 12 measures of superutilization that mapped to the four superutilization dimensions. V.1 lists the 12 measures and the four dimensions associated with each. The measures listed are defined based on the available data. However, it should be noted that the definition of these measures for Tennessee

[3] For Florida, eligibility was determined based on the first out-of-home placement that occurred within the study window. We implemented this approach because the structure of the Florida data included out-of-home placements and in-home placements that were in the same custody episode.

and Florida differ slightly depending on the specific data available for each site. For example, under the cost dimension, we included two cost measures—*Total placement cost per year* and *Service cost per year*—that refer to the total cost of out-of-home placements per year and the cost of child welfare services per year, respectively. Cost information for out-of-home placements and services was available from the Tennessee DCS; however, we did not receive placement and services cost information from Florida OCW. However, we received Eckerd CBC-purchased service cost information for Florida. Thus, we were not able to use a placement cost measure for Florida in the analysis, but we were able to include a more limited service cost measure for children who received Eckerd CBC-purchased services. Similarly, separate data on mental health services and substance abuse services outside of Medicaid were available for Florida but were not available for Tennessee. Therefore, we could only include non-Medicaid substance abuse mental health service measures in the Florida analysis. A summary of the measures of superutilization, their definitions, and how they were constructed is provided in Section D, below; a comprehensive list that includes measures we constructed but did not use in the final latent class analysis based on early empirical investigation is included in Appendix B.[4]

V.1. Superutilization dimensions and associated measures

	Superutilization Dimension			
Type of measure	**Frequency / dosage**	**Duration**	**Intensity**	**Cost**
Child welfare custody/placements	Total number of episodes Total number of placement moves	Total episode length of stay	Average share of time in group home care	Total placement cost per year
Child welfare services	Child welfare services per year			Service cost per year
Medicaid services	Emergency services per year Inpatient services per year Outpatient services per year			
Other substance use / mental health services (SAMH)	Mental health services per year Substance abuse services per year			

Note: Child welfare services for Florida refer to the CBC-purchased services provided by Eckerd.

C. Measuring superutilization

After constructing the variables, the next phase of the process involved measuring superutilization. As discussed in Chapter I, to our knowledge, the literature on studies of superutilization in the child welfare context is not extensive, limiting our ability to draw on well-established measurement practices in the field. As such, we relied on guidance from subject matter experts within the project team. We supplemented this feedback with insights from the Medicaid research literature, which includes studies that examine high utilization of health care services among beneficiaries. Drawing on these sources, the key goal was to formulate a measure

[4] The Medicaid data for both Tennessee and Florida enabled us to examine physical health and behavioral health services separately. As part of our measurement of superutilization, we constructed separate physical health and behavioral health service counts by inpatient, outpatient, and emergency service category. Based on our initial empirical analysis, however, we determined that these additional variables did not provide useful additional information for the latent class analysis that is discussed in Chapter VII. Although these measures are not listed here, information on their construction is provided in Appendix B.

of superutilization that was both consistent with the multidimensional nature of the concept and empirically rooted in the child welfare and Medicaid data available to us.

Ultimately, our goal was to create a subsample of children whom we defined as those experiencing superutilization for each site. We created our superutilization samples for each site by establishing threshold values for each variable listed in V.1 and then identifying children who either met or surpassed those threshold values for any given variable. Given differences in data availability, we identify slightly different measures of superutilization for each site. Below, we discuss our approach to establishing the thresholds that we used to create the superutilization sample.

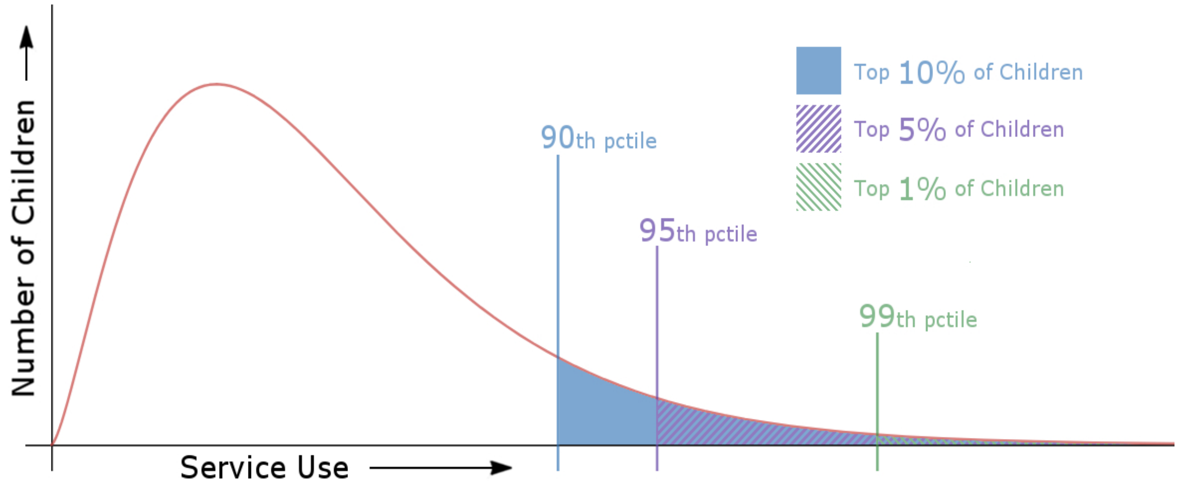
1. Thresholds for defining superutilization

The approach used to define threshold values was based on our conceptualization of superutilization. As noted above, we view superutilization as consisting of service utilization or receipt at a high level compared to the rest of the sample. To make this conceptualization more concrete, Figure V.1 provides a visual representation of child welfare service use. Specifically, the figure depicts the distribution of a given child welfare service (or bundle of services) over a hypothetical population of children in the child welfare system. On the x-axis, the quantity of the service is bound by zero on the left to a non-bounded upper limit on the right. Accordingly, movement from left to right indicates higher service use. The y-axis represents the probability density of the number of children in the system who are eligible for the service. Movement up the y-axis indicates a larger number of children in the corresponding distribution.

There are several key features of this distribution worth noting. First, the peak of the curve corresponds with the highest number of children on the y-axis but with a lower level of service use on the x-axis. This indicates that the majority of children eligible for the service do not necessarily utilize a high level of the service. Although the peak of the curve is centered to the right of zero, showing that all children utilize some level of the service, that level is likely to be low (that is, closer to zero). A second point is that the utilization of the hypothetical service is not normally distributed across the population of eligible children. The distribution of service use in Figure V.1 is not symmetrical. It has a long right tail, suggesting that a small number of children in the population use a large number of services.[5] This is consistent with the idea that high levels of service utilization, which is central to the concept of superutilization, likely apply to a small subset of children who may have specific needs. However, an important caveat is that the hypothetical distribution shown in Figure V.1 only depicts service use and does not provide any representation of need. Our conceptualization of superutilization only focuses on service use and does not explicitly address the issue of whether high levels of service utilization are appropriate for the level of need.

[5] Figure V.1 is a based on a chi-squared distribution with five degrees of freedom. This was chosen in order to produce a nonsymmetrical peak in the curve and to emphasize the skewness in the right tail of the distribution. Visualizing and modeling service utilization as a long-tailed distribution (for example, gamma) is also consistent with many applications in health care research (see Mihaylova et al. 2011).

Figure V.1. Hypothetical distribution and thresholds of child welfare utilization



The relationship depicted in Figure V.1 also highlights our approach to defining superutilization. Along the right tail of the service use distribution, we show three thresholds that signify progressively higher levels of relative service use. The first threshold is the 90th percentile of the distribution. This means that children whose level of service use is at this threshold constitute the top 10 percent of service users in the eligible population. The next set of threshold values proceed along the continuum in terms of higher levels of service use. The 95th and 99th percentiles, for example, translate into the top 5 and 1 percent, respectively, of children along the service use continuum. These were the key threshold points that we considered when deciding where to draw the line between defining a child as experiencing superutilization of services or not.[6] Consistent with our original conceptualization, the use of any of these thresholds expresses superutilization as being relative to an observable cut point even though the actual value of that point could vary for any given measure. The key decision was which threshold to choose.

Ultimately, we used the 90th percentile value of the variables as the threshold for determining superutilization status. Specifically, if a child was at or above the 90th percentile value for any of the variables listed in V.1, we flagged that child as experiencing superutilization

[6] An alternative approach that the team considered to selecting thresholds was to use a rule that specifies an absolute value of the variable as a cut point. This approach relies primarily on subject matter expertise to define a meaningful value for what constitutes high utilization for a given measure. Although we considered this approach, we preferred a more data-driven procedure that allowed the decision on thresholds to be rooted in actual distributions of the variables. The data-driven approach was also preferable because it reduced the potential for bias due to subjectivity to affect the thresholds. In this respect, we considered relying on actual distributions in the data to define thresholds to be a more objective and transparent approach.

for that measure.[7] The decision to use the 90th percentile was based primarily on two considerations.

First, we sought to maximize the likelihood of correctly identifying children with high levels of service utilization, by identifying a level of service use that is hard to dispute as being sufficiently high and also minimizing the risk of incorrectly excluding children with high levels of utilization. Thus, in using the 90th percentile, we tried to balance the risk of being sufficiently inclusive with also being responsibly exclusive to ensure that the measured concept of superutilization was analytically meaningful. A key concern with using a higher threshold value, such as the 95th or 99th percentile, was that this might be overly restrictive and might exclude children who exhibit similar utilization patterns but may have just missed the cutoff. In contrast, the potential risk of setting too low a threshold (for example, at the 80th percentile) would be to include children who may not truly be superutilizers (that is, increasing the number of false positives). The challenge we faced is that any choice of threshold constitutes a judgement about defining where to draw the line in terms of particularly high service utilization. In our judgement, the 90th percentile (or top 10 percent of children) provided the optimal balance between including children with sufficiently high service use patterns while also excluding children whose utilization was lower.[8]

Second, to balance the team's collective judgement with more established practices in other research fields, we also examined the literature on health service utilization in the context of Medicaid. This review reinforced our choice of the 90th percentile as the key threshold for measuring superutilization. The general research literature on Medicaid consistently uses the 90th percentile as a defining cutoff for high levels of health service utilization and cost. Billings and Mijanovich (2007), for example, examine Medicaid beneficiaries at a high risk of future hospitalization defined by a tiered threshold of those in the 50th, 75th, and 90th percentiles with those in the top decile considered the highest utilizers. Similarly, the 90th percentile is commonly used as a cutoff in models predicting which Medicaid beneficiaries will likely have higher future high health needs. Predictive models developed by Weir et al. (2008), Leininger et al. (2014), and Wherry et al. (2014) all define high-needs beneficiaries as those in the top decile of various utilization categories, including chronic conditions, emergency department visits, and cost. In addition, studies that may be considered closer analogues with respect to the focus on children, such as research on Medicaid pediatric patients with high health needs, also use the 90th percentile as the threshold value for high service use (Leininger et al. 2015). In summary, we believe the use of the 90th percentile threshold for defining superutilization in the child

[7] The 90th percentile refers to the top decile of the value of the variable, not necessarily to the top decile of children. In practice, the percentage of children who meet the 90th percentile threshold on a given measure may be higher or lower than 10 percent of the population.

[8] We also considered using a threshold based on the number of standard deviations above the mean value of a given measure. For example, one could specify the threshold to be two standard deviations above the mean. This approach has the advantage of basing the threshold on a well-established statistical criterion. However, one potential downside is that the standard deviation-based threshold is less intuitive for practitioners and, depending on the extent of variation in any given sample, could produce very different cutoff values across different samples. For this reason, we decided to rely on the more intuitive and widely used percentile-based threshold.

welfare context is justified on the basis of informed judgement, relative ease of interpretation, and consistency with the approach taken in similar research literatures.

2. Additional adjustments to superutilization measures

Having established the threshold values for determining superutilization, the final step in the measurement process involved either age-adjusting the variables listed in V.1 or converting them to annualized rates. This additional adjustment step was performed before calculating the 90th percentile cutoff value for each variable.[9] The primary reason for adjusting these variables was to account for patterns in the data that may be artifacts of either the age distribution of the child sample or the timing of the study window (2011–2015 for Tennessee and 2013–2015 for Florida). These adjustments are briefly discussed below.

a. Age-adjustment

As discussed in Chapter I, our approach to conceptualizing superutilization focused on utilization of services beyond a certain threshold. In parallel, our approach also centered on the idea that children of any age in out-of-home placements could potentially experience high levels of service use. This idea may be particularly important for child welfare agencies that are interested in identifying early signs of or potential risk factors associated with superutilization. Accordingly, a child's level of utilization relative to his or her peers within the same age group may be of interest. Our approach to measuring superutilization assumes that this is the case. Our approach to age adjustment is thus intended to ensure that our superutilization measures are not skewed by age; in particular, we tried to ensure that the definition of superutilization was not directly tied to age.

One potential risk of calculating the 90th percentile threshold for an unadjusted variable that is measured over the lifetime of a child is that certain children may be more likely to meet or surpass the threshold based solely on their age. For a measure such as *Total number of placement moves* in V.1, for example, younger children in out-of-home placements may be less likely to meet the 90th percentile threshold simply because they have not had a sufficient opportunity to experience a high number of placement moves. As a result, the probability of being identified as a child who experienced superutilization on this measure may be primarily a function of a child's age, with older children more likely to be flagged than younger ones. Without age-adjusting the threshold values, the superutilization sample may skew older, which could be primarily a function of the correlation introduced between age and the likelihood of experiencing a high number of placement moves.

To address this potential measurement problem, we age-adjusted the four variables listed in V.1 that were most likely to introduce correlations between high superutilization threshold values and age: (1) *Total number of placement moves*, (2) *Total number of episodes*, (3) *Total episode length of stay,* and (4) *Average share of time in group care*. To age-adjust these four lifetime variables (i.e., we included data before the beginning of the study window, when

[9] When calculating the 90th percentile thresholds, we only included sample members with custody and service spells that ended within the study window (that is, were not right-censored). We implemented this approach to avoid including ongoing spells that might introduce noise into the variable distributions used to identify the superutilization thresholds.

available for these measures), we first stratified each variable by a specific age based on a child's age at exit at the end of the study window or at the time of last contact with the child welfare system. For each variable, this resulted in ages ranging from 0 to 23 years. Within each specific age (starting at less than 1 year old up to age 23), we examined the distribution of the variables to determine the 90th percentile value that was specific to that age group and that variable. Thus, the superutilization threshold was set within each age group-variable combination resulting in specific cutoff values for each combination. Consequently, the superutilization indicators were defined relative to each age group for all four variables. This approach minimized the risk of conflating our measurement of superutilization with a child's age.

b. Annualizing rates for cost and service measures

In addition to age, a similar concern centered on the measurement of child welfare and Medicaid service utilization and cost. In most cases, these measures are based on the number of services received or the total cost of a given service or placement. The potential risk with basing the superutilization threshold values on simple frequencies or dollar amounts is that higher values on these measures may be a function of time in the study window. Specifically, some children included in our sample may have entered child welfare early in the study window (for example, in 2011 for Tennessee and 2013 for Florida). If a child remained in the child welfare system through the end of the study window (2015 for both samples), the risk of accumulating a higher number of services, placements, or costs could similarly increase. In turn, this might increase the probability of being identified as a child experiencing superutilization of services based on the 90th percentile threshold. Conversely, a child who entered the system later in the study window would have less time to accumulate services and costs, making that child less likely to be identified as experiencing superutilization of services. However, with more time to accumulate services, it is possible that a child who enters the study sample late might eventually experience superutilization of services.

The key issue, then, is that exposure to the study window may affect the likelihood of a child being identified as one who experiences superutilization of services. Exposure to the study window is an arbitrary function of data availability for both Tennessee and Florida and may not be a true reflection of high utilization patterns compared to others who may have entered the study sample later by chance.

To address this potential measurement problem, we transformed the eight service and cost variables listed in V.1 into annualized rates for each eligible sample member: these variables are denoted with the suffix *per year*. For the child welfare services variables, the rates were calculated using the number of service start dates within the study window divided by the duration of time (in days) from either the first service or placement that the child received from the child welfare system. For Medicaid services variables, the rates were calculated using the number of service start dates that occurred during out-of-home placements that started during the study window divided by the duration of time (in days) in which the child was in out-of-home placements during the study window. The cost variables were transformed into rates using the total cost of services or placements that started in the study window divided by the number of days that child was in contact with the child welfare system. These ratios were then multiplied by 365 to produce an annualized rate for both services and costs. In calculating these rates, we included right-censored cases (those cases that continued after the study time period ended) and used the end date of the study period to calculate contact duration if the case was right-censored. All right-censored cases were included in count variables (child welfare services, Medicaid services, and SAMH services). Placement costs were prorated so the portion of time after the end of the study window was excluded. Child welfare service costs were not prorated in Tennessee, where a service start and end date were provided. We were unable to prorate Eckerd services in Florida because the data only included a single payment date. We excluded left-censored cases for all measures *except* the SAMH measures. Left-censored cases were retained for the SAMH measures due to concerns that excluding these cases would also exclude individuals in long-term substance abuse or mental health treatments whose experiences are of policy interest.

Similar to the rationale for age-adjustment, transforming variables based on counts and dollar amounts into annualized rates controls for a sample member's exposure to the study window. In this case, the denominator is based on observed eligibility to receive a service or accrue a cost, and thus standardizes the measure based on exposure. Using this approach, we calculated the 90th percentile threshold values for the annualized rates in order to identify children who experienced superutilization for the service and cost variables. Appendix B provides more details on each of the variables.

3. Superutilization measures by site

As discussed in Chapter I, a key goal of this exploratory analysis is to examine whether there are different types of superutilization. To address this question empirically, we maintained the disaggregated structure of our measures of superutilization. We opted to use this approach rather than combine similar variables prior to analysis because the primary interest was to assess how different measures of superutilization may cluster together to help define latent classes. In order to do this, the structure of the observed variables (our measures of superutilization) should remain disaggregated to maximize the ability of our analysis to uncover patterns of superutilization. As discussed in Chapter VII, we used latent class analysis to define types of superutilization based in part on the (unobserved) correlational structure of the disaggregated data. In the remainder of this chapter, we briefly describe how we constructed the superutilization measures that were used for the descriptive and latent class analysis and discuss the sample sizes for the Tennessee and Florida analyses.

a. Applying superutilization threshold criteria

Applying the 90th percentile threshold criterion to the Tennessee and Florida out-of-home custody samples produced a design matrix of 1s and 0s for all sample members across all variables. Specifically, for each sample member, a value of 1 indicated that the 90th percentile threshold was satisfied for a given variable, whereas a value of 0 indicated that the criterion was not satisfied. Any sample member with a value of 1 on any variable was considered a child who experienced superutilization and was thus included in the superutilization sample. By contrast, sample members who had values of 0 on all variables were not considered to experience superutilization. Therefore, the sample of children identified as experiencing superutilization will be the total number of children identified by any one of the superutilization measures.

D. Superutilization sample sizes in Tennessee and Florida

Tables V.2 and V.3, below, provide the summary of measures used to define superutilization for the Tennessee and Florida samples, respectively. These measures are the specific variables that were used to identify superutilization in the Tennessee and Florida samples. Both tables summarize the variable names, descriptions, 90th percentile threshold values of the variables, and the sample size and percentage at or above the threshold value. More specifically, this depicts the mean and standard deviation of each measures and the 90th percentile cutoff value, which was used to identify those experiencing superutilization. As noted above, the 90th percentile refers to the top decile of the distribution of values for a given variable; it does not necessarily translate to the top decile of children in the population, though the proportions are usually close. In Tables V.2 and V.3, it is important to note that to efficiently depict the threshold values for age-adjusted variables, we depicted a pooled average, rather than depict each age-specific value that was used to identify who was experienced superutilization for each age. The final column for Tables V.2 and V.3 shows the number and percentage of the sample who were at or above that threshold and therefore identified as experiencing superutilization for that measure. An important point to note is that for any given measure, the proportion of children identified as experiencing superutilization is relatively low. In Tennessee, for example, the percentage of children identified as being at or above the threshold ranges from a low of 5.5 percent (for Medicaid inpatient services per year) to a high of 15.6 percent (for the total number of placement moves). Similarly, for Florida, the percentage ranges from a low of 2.6 percent (for child welfare service costs per year) to a high of 16.1 percent (for the total number of placement moves). However, despite the relatively low proportions of children identified for any given measure, the total number of individual children who are identified as experiencing superutilization for *any* specific measure is high, as reported in the last row of both tables. Below, we discuss the most likely reason for this result.

V.2. Tennessee sample: Descriptions, thresholds, and percent of sample identified as experiencing superutilization for each measure

	Variable description	Superutilization dimension	Mean (Std.Dev)	90th pct threshold value	Number (percent) of total sample identified as experiencing superutilization (at or above 90th pct)
Total number of custody episodes[a]	Total custody episodes in the child welfare system (age-adjusted with minimum cutoff of 2)	Frequency/ dosage	1.162 (0.452)	2	3,190 (14.7%)
Total number of placement moves[a]	Total number of placement moves across all episodes (age-adjusted)	Frequency/ dosage	3.218 (2.769)	6	3,387 (15.6%)
Total length of stay in out-of-home custody[a]	Total days in out of home custody across all episodes (age-adjusted)	Duration	401.188 (375.098)	872	2,722 (12.6%)
Average share of time in group home or congregate care[a]	Average share of time spent in group home or congregate care among all out-of-home placements (age-adjusted)	Intensity	7.098 (21.146)	24.138	1,827 (8.4%)
Child welfare services per year[a]	Number of child welfare service starts during contact with the child welfare system excluding case management (calculated as annual rate)	Frequency/ dosage	4.652 (6.695)	11.310	2,432 (11.2%)
Total placement cost per year[a]	Total cost of child welfare placements in custody (calculated as annual rate)	Cost	$18,217.72 (20,898.82)	$39,597.69	2,552 (11.8%)

	Variable description	Superutilization dimension	Mean (Std.Dev)	90th pct threshold value	Number (percent) of total sample identified as experiencing superutilization (at or above 90th pct)
Child welfare service cost per year[a]	Total cost of child welfare services per year (calculated as an annual rate)	Cost	$1,370.888 (3,261.14)	$3,363.44	1,789 (8.3%)
Medicaid inpatient services per year[b]	Number of Medicaid inpatient physical and behavioral health services (calculated as annual rate)	Frequency/ dosage	0.101 (1.265)	0! (1,257)	1,257 (5.8%)
Medicaid outpatient services per year[b]	Number of Medicaid outpatient physical or behavioral health services (calculated as annual rate)	Frequency/ dosage	14.661 (19.140)	37.960	2,261 (10.4%)
Medicaid emergency services per year[b]	Number of Medicaid physical and behavioral emergency health services (calculated as annual rate)	Frequency/ dosage	0.990 (4.078)	2.325	2,213 (10.2%)
Superutilization sample size					**12,332 (56.9%)**

Source: [a]Tennessee DCS; [b]Tenncare.

Note: The mean, standard deviation, 90th percentile cutoff value, and number of children at or above the cutoff value are based on the distributions for the pooled study sample that exclude right-censored custody or services. As noted in this chapter and where indicated in the description section of the table, the actual means, standard deviations, and cutoff values for certain measures are based on age-adjusted values for children in the sample. This means that the cutoff values are relative to a child's age cohort, which may be different than the cutoff value for the pooled sample. The age-specific values for all variables that were age-adjusted were used to define the study sample. The sample sizes of children identified as experiencing superutilization for the age-adjusted measures reported are based on the total number identified from the age-specific cutoff values.

! When the 90th percentile value is zero, the next positive value was used to establish the cutoff point for defining superutilization.

V.3. Florida sample: Descriptions, thresholds, and percent of sample identified as experiencing superutilization for each measure

Variable	Description	Superutilization dimension	Mean (Std.Dev)	90th pct. threshold value	Number (percent) of total sample identified as experiencing superutilization (at or above 90th pct)
Total number of custody episodes[a]	Total number of custody episodes with at least one out-of-home placement (age-adjusted; minimum cutoff of 2)	Frequency/ dosage	1.206 (0.495)	2	894 (13.4%)
Total number of placement moves[a]	Total number of placement moves across all episodes with at least one out-of-home placement (age-adjusted)	Frequency/ dosage	3.923 (5.034)	7	1,078 (16.1%)
Total length of stay in out-of-home custody[a]	Total days in out-of-home placements across all episodes in the child welfare system (age-adjusted)	Duration	334.669 (304.149)	676	740 (11.1%)
Average share of time in group home or residential treatment placements[a]	Share of time in group home or residential treatment placement among total days in out-of-home placements over a lifetime (age-adjusted)	Intensity	5.900 (20.255)	9.639	609 (9.1%)

Variable	Description	Superutilization dimension	Mean (Std.Dev)	90th pct. threshold value	Number (percent) of total sample identified as experiencing superutilization (at or above 90th pct)
Child welfare CBC-purchased services per year[b]	Total number of child welfare CBC purchased services (Eckerd) during contact duration with child welfare (calculated as annual rate)	Frequency/ dosage	1.237 (5.568)	2.491	601 (9.0%)
Child welfare CBC-purchased service cost per year[b]	Total cost across all child welfare CBC-purchased services (Eckerd) (calculated as annual rate)	Cost	$535.65 (5,494.92)	$434.52	567 (8.5%)
Mental health services per year[d]	Number of mental health treatment episodes over contact duration with child welfare system (calculated as annual rate)	Frequency/ dosage	2.212 (9.603)	1.763	560 (8.4%)
Substance abuse services per year[d]	Number of substance abuse treatment episodes over contact duration with child welfare system (calculated as annual rate)	Frequency/ dosage	1.302 (7.733)	0!	262 (3.9%)
Medicaid inpatient services per year[c]	Number of Medicaid inpatient physical and behavioral health services (calculated as annual rate)	Frequency/ dosage	0.136 (0.887)	0!	380 (5.7%)
Medicaid outpatient services per year[c]	Number of Medicaid outpatient physical and behavioral health services (calculated as annual rate)	Frequency/ dosage	14.017 (24.579)	32.301	762 (11.4%)
Medicaid emergency services per year[c]	Number of Medicaid emergency physical and behavioral health services (calculated as annual rate)	Frequency/ dosage	0.933 (3.321)	2.281	779 (11.6%)
Superutilization sample size					**3,726 (55.7%)**

Source: [a]Florida OCW; [b]Florida Eckerd; [c]Florida ACHA; [d]Florida SAMHIS.

Note: The mean, standard deviation, 90th percentile cutoff value, and number of children at or above the cutoff value are based on the distributions for the pooled study sample that exclude right-censored custody or services. As noted in this chapter and where indicated in the description section of the table, the actual means, standard deviations, and cutoff values for certain measures are based on age-adjusted values for children in the sample. This means that the cutoff values are relative to a child's age cohort, which may be different than the cutoff value for the pooled sample. The age-specific values for all variables that were age-adjusted were used to define the study sample. The sample sizes of children identified as experiencing superutilization for the age-adjusted measures reported are based on the total number identified from the age-specific cutoff values.

! When the 90th percentile value is zero, the next positive value was used to establish the cutoff point for defining superutilization.

Because a central part of our approach centers on accounting for and measuring different components of superutilization, we have included numerous measures in our analysis. However, many of these measures have limited overlap with each other, meaning that children identified as experiencing superutilization on one measure may not be the same children identified as experiencing superutilization on another measure. To assess the extent of dimensionality among the superutilization measures, we examined all pairwise correlations between superutilization measures for Tennessee and Florida. The intuition behind this approach is that high correlations between measures should be an indication of overlap. If pairs of variables exhibit high correlations then this might suggest a high degree of overlap. A high degree of overlap between variables might increase the probability that children identified for superutilization on one measure may also be identified on other highly correlated measures. Conversely, low correlations suggest less overlap and, consequently, an expectation that fewer children might be identified for superutilization on multiple measures.

Our examination of all pairwise correlations for Tennessee showed coefficients ranging from a low of -0.287 (between total number of episodes per year and number of services per year) to a high of 0.718 (between total service costs per year and total number of services per year). However, the average of the pairwise correlations for all groups of variables for the Tennessee sample ranged from -0.033 to 0.184. For Florida, the pairwise correlations ranged from a low of -0.155 (between out- of-home episodes length and stay and Medicaid emergency services per year) to a high of 0.615 (between total number of episodes and the out-of-home length of stay). Similarly, the average pairwise correlations for all groups of variables for the Florida sample ranged from -0.026 to 0.228. For the overwhelming majority of measures, the correlation coefficients were only slightly above or below zero. Intuitively, the relatively wide range of correlation coefficients combined with a low group average across all pairwise comparisons underscores the lack of a clear pattern in terms of the strength of overlap between the measures. Although for some pairs of measures, such as the number of services and service cost, the relatively high correlations are not surprising, we interpret the general absence of consistently high or low correlations across all measures as evidence of low overlap between measures. We believe this is indicative of high dimensionality among the measures, thus increasing the probability that distinct children may be identified as experiencing superutilization on different measures.

Ultimately, the relatively large number of measures, along with the general lack of high positive (or negative) correlations between them, means that the probability of a child being identified as a superutilizer for at least one measure is generally higher than would be the case if fewer measures were used or if the correlations between measures were higher. However, this high dimensionality of superutilization is precisely what we focus on in Chapter VII, which introduces and summarizes the results from our latent class analysis. Those results will help to underscore how high dimensionality translates into distinct latent classes. Another way to look at the lack of overlap between classes is that among the children who experience at least one form of superutilization, about half of these children in Tennessee (54.1 percent) and Florida (49.5%) achieve superutilization in more than one category.

Furthermore, our use of the 90th percentile threshold for the measurement of superutilization is a more inclusive approach compared to using higher percentile values that would identify fewer children. This decision was informed by our desire to minimize the likelihood of not identifying children who experience superutilization of services, since using a more stringent criterion would identify fewer children but also increase the risk of missing children who experience high use of services or using a threshold others can argue may be too stringent.

As a result of the dimensionality of the superutilization measures and use of 90th percentile threshold for the superutilization measures, we obtain a relatively large number of children who are identified as experiencing superutilization on at least one measure. For the Tennessee sample, 12,332 children (56.9 percent of the sample), among those with out-of-home custody episodes starting between July 2011 and December 2015, were identified as experiencing superutilization. For the Florida sample, 3,726 children (55.7 percent of the sample), among those with out-of-home custody episodes starting between September 2013 and December 2015, were identified as experiencing superutilization.

As an additional sensitivity check, we also examined the number and proportion of children who would be identified as experiencing superutilization if we used the 95th percentile rather than the 90th. For Tennessee, the 95th percentile threshold would identify 8,866 children as experiencing superutilization, which translates to 40.9 percent of the out-of-home custody sample. For Florida, the 95th percentile threshold would identify 2,691 children as experiencing superutilization, which constitutes 40.2 percent of the sample. Overall, this suggests that even using a higher threshold would still result in a substantial proportion of children being identified as experiencing superutilization. Again, we attribute this primarily to the large number of non-overlapping variables we examine for superutilization.

VI. CHARACTERISTICS OF CHILDREN WHO EXPERIENCE SUPERUTILIZATION OF SERVICES

A. Introduction

This chapter describes the characteristics of those identified as superutilizers among the study samples for each site, using the measurement approach discussed in Chapter V. Specifically, this chapter aims to address the following research question:

- What are the distinguishing characteristics of children who experience superutilization of child welfare and other services?

Among the Tennessee sample, 12,332 (56.9 percent) children were identified as experiencing superutilization of services, whereas among the Florida sample, 3,726 (55.7 percent) children were identified as experiencing superutilization of services. Children in the superutilization sample are those who met the criteria of the 90th percentile or higher for at least one of the superutilization measures (as discussed in Chapter V) at some point within the study window.

The following sections highlight characteristics and child welfare outcomes of those who experience superutilization and also describes their service usage, which is generally expected by definition to be higher among those who experienced superutilization. Results are discussed separately for Tennessee and the three-county region in Florida. All results in this chapter were based on descriptive analysis using SAS. To test for statistical significance, we used t-tests for continuous measures and chi-squared tests for categorical measures. When cell sizes were too small, we used Fisher's exact tests. Although we corrected for multiple comparisons, there is still a chance that the Type I error rate (rejecting a true null hypothesis) could be inflated, so caution should be exercised when interpreting a significant result. While the following sections present key findings, the full set of results can be found in Appendix C.

B. Tennessee superutilization sample

1. Characteristics of those experiencing superutilization

In regard to demographics, we find that adolescents, ages 13 through 17, are the highest proportion of children identified as experiencing superutilization (34.0 percent); this is greater than the percentage of adolescents identified among those who did not experience superutilization (20.5 percent). We find these differences regarding age, even after age-adjusting several key superutilization measures. Similar percentages of males and females are identified as those who experienced superutilization (51.6 percent and 48.4 percent, respectively) compared to those who did not (49.6 percent and 50.4 percent, respectively). Given cautions by DCS in regard to data quality on race and ethnicity information, we do not discuss results for those demographics.

When looking across DCS regions at the distribution of children who experienced superutilization and those who did not, we see similar distributions. The one exception is that children experiencing superutilization of services have the highest percentage (12.7 percent) identified from the Special Investigations Unit, which are children currently in foster care being investigated for child maltreatment; this percentage is much less (6 percent) among those who did not experience superutilization. All results regarding children who experienced superutilization and those who did not and their distribution across DCS regions can be found in C.3 in Appendix C.

We find several similarities and differences among those experiencing superutilization and those who did not in regard to the reasons associated with their removal from home and entry into foster care, which was only available for the Tennessee sample. We find similar percentages of those experiencing superutilization and those who did not among children with the following reasons for removal: neglect (37.7 percent and 38.0 percent, respectively), physical abuse (11.9 percent and 10.4 percent, respectively) and sexual abuse (5.5 percent and 5.9 percent, respectively), as well as several other reasons. In regard to key differences, a higher percentage (18.8 percent) of children with superutilization compared to those without superutilization (6.2 percent) have child's behavior problem identified as a reason for removal. However, for those with parental drug abuse as a reason for removal, we find a lower percentage (35.4 percent) among children with superutilization than among those without (42.4 percent).

Though limited in availability, in regard to assessment scores for the Tennessee sample, we find higher needs among those with superutilization compared to those without superutilization for two of the assessments. However it is important to note that only a small subset of the sample had data on assessment scores. Specifically, we find higher percentages of children with higher levels of CANS scores among those experiencing superutilization than among those who did not, indicating higher needs among children with superutilization. Also, we find a lower average score on the Ansell-Casey Life Skills assessment among those with superutilization (25.1) compared to those without superutilization (40.2), indicating those with superutilization on average have less developed life skills. However, we find similar percentages among both groups for FAST scores, which assess families' needs; the YLS assessment average scores, measuring adolescent risks and needs, are also similar for each group.

We also looked at differences among children who experienced superutilization and those who did not in regard to whether they exited custody and their permanency type. A lower percentage (65.6 percent) of children with superutilization exited custody during the study window compared to those not experiencing superutilization (76.2 percent). In comparing types of permanency among those who exited custody, a higher percentage of youth experiencing superutilization emancipated (11.4 percent) compared to those that do not experience superutilization (4.7 percent). However, there are lower percentages of those with superutilization than those without who achieved guardianship (4.0 percent and 8.3 percent, respectively) or relative/kinship placements (18.4 percent and 22.1 percent, respectively).

2. Definitional characteristics of service use among those experiencing superutilization

Although the focus on the research question was to identify characteristics of those who experience superutilization, we also assessed differences among key definitional characteristics that were used to identify superutilization, including number of child welfare episodes and placements as well as number and type of child welfare and Medicaid services. As we anticipated, overall, those identified as experiencing superutilization have higher percentages of children with higher levels of service use on each of these measures compared to those who did not experience superutilization. These findings are consistent with our identification of superutilization on these definitional characteristics regarding high levels of service use.

C. Florida superutilization sample

1. Characteristics of those experiencing superutilization

When assessing demographic characteristics of children in the Florida sample, even after we age-adjusted for key superutilization measures, we find higher percentages of children (20.2 percent) among those experiencing superutilization who were teens, ages 13 through 17, compared to those who did not experience superutilization (9.6 percent). However, we find lower percentages (29.6 percent) of children ages 1 to 6 years among those with superutilization compared to those without (41.4 percent). We also find a greater percentage of males (53.4 percent) identified as experiencing superutilization than those who did not (48.1 percent). We do not find any racial differences among those who experienced superutilization and those who did not. Also, we find similar distributions of children across Hillsborough, Pasco, and Pinellas counties among those who experienced superutilization and those who did not.

In regard to assessments for the Florida sample, we caution interpretation of these assessment scores given the small number of children in the sample with these scores. We do not find large differences in the OCW investigational risk levels among children with this assessment who were experiencing superutilization and those who did not experience superutilization. Among those with CFARS assessments, for both the overall score and security domains score, we find lower percentages of children with low scores among those with superutilization compared to those who did not have superutilization. For FARS and ASAM assessments, we generally see higher percentages among those with superutilization than among those who did not have superutilization;

In addition, we compared child welfare permanency rates among those with superutilization and those without. We find roughly the same percentage of children exited custody for both groups. However, we find a few differences in regard to the type of permanency. Specifically, higher percentages of children experienced adoption (13.6 percent) among those with superutilization than those who did not (6.0 percent). Also, we find a lower percentage of children (63.0 percent) experienced reunification among those with superutilization than those who did not have superutilization (74.8 percent).

2. Definitional characteristics of service use among those experiencing superutilization

We also compared the differences among key definitional characteristics that were used to identify superutilization. Specifically, we assessed differences among those with and without superutilization in regard to the number of child welfare episodes and placements, as well as the number and type of child welfare CBC-purchased services, Medicaid services, and other substance abuse and mental health services. As we expected and is consistent with our measurement approach, in general, those identified with superutilization have higher percentages with higher levels of service use on each of these measures compared to those without superutilization.

D. Discussion and implications

This analysis provides insights regarding demographic and other characteristics among those identified as experiencing superutilization of services. In particular, given the consistent findings regarding age for both sites, potential areas on which to focus efforts to monitor or address superutilization may be among those children who are teenagers, though early intervention could have a large impact on superutilization in the later years for certain groups of children. We also find that some of the assessment scores indicated higher levels of need among those identified as experiencing superutilization. Therefore, we will want to assess the predictive potential of certain kinds of assessments to identify superutilization, which is discussed in Chapter VIII. Findings regarding the reasons for removal are less clear regarding implications for practice. The study findings are a starting point for ongoing work with the sites by Casey's Strategic Consulting and Research teams.

VII. TYPES OF SUPERUTILIZATION

A. Introduction

In the previous chapters, we outlined our approach to measuring the concept of superutilization and provided the results of our descriptive analyses identifying characteristics of children who experience superutilization. These results set the stage for more in-depth examination of children experiencing superutilization in the Tennessee and Florida samples. By exploring the possibility of distinct patterns of high service use among children who experienced out-of-home custody, this chapter attempts to provide further insights that may help policymakers and program staff better serve the needs of children in the child welfare system. The primary objective of this chapter, therefore, is to answer the following research question:

- Are there different types of superutilization? Specifically, are there types of superutilization based on frequency, duration, intensity, or cost of services?

Although our approach to addressing these questions is descriptive in nature, the insights may help inform deeper understanding of the complex patterns of service use among children in child welfare custody. The results highlighted in this chapter may also refine models that are intended to predict the probability of experiencing superutilization, which we discuss in the next chapter.

The remainder of this chapter is organized as follows. First, we provide a brief overview of our latent class analysis (LCA) to examine types of superutilization. Next, we provide the results of our final latent class models separately for Tennessee and Florida and summarize key highlights for each of the identified latent classes. Finally, the chapter concludes with a discussion of the implications of our analysis for policy and practice within the child welfare system.

B. Overview of methodological approach

To examine whether there are distinct types of superutilization, we used LCA. More formally, LCA is a form of structural modeling designed for multivariate categorical data. A key goal of LCA is to identify and characterize clusters (or classes) of similar cases for data that are observed as a series of categorical response values (Linzer and Lewis 2011). Intuitively, the goal of LCA is to determine whether a given dataset contains only one population or a mixture of several populations that can be uncovered by examining patterns in the observed variables. Typical applications may include, for example, assessing whether individuals' responses to attitudinal measures on survey items can meaningfully classify respondents into different attitude clusters.

The measures used in our analysis are well suited to latent class modeling because, for each child in the superutilization sample, every variable is coded dichotomously to reflect the presence (1) or absence (0) of satisfying the 90th percentile threshold on the measures of superutilization. This produces a design matrix of 1s and 0s for all combinations of superutilization measures for all sample members. In the parlance of LCA, these measures constitute the "manifest" (observed) variables that are used as inputs in the modeling process. The latent class model, then, stratifies the cross-classification of these observed variables by a latent (unobserved) categorical variable that eliminates the correlation and dependence between the observed variables; thus, the observed variables are assumed to be independent of each other conditional on the values of the latent class (also known as the local or conditional independence assumption) (Collins and Lanza 2013; Nagin 2005; Linzer and Lewis 2011).

The latent class model assigns each sample member probabilistically to a latent class.[10] However, while each sample member has a probability of assignment for all latent classes, sample members are ultimately assigned to the class for which their predicted probability of membership is highest. Thus, each sample member is placed in only one latent class and all classes are mutually exclusive. The differences between children who experience superutilization in the frequency, duration, intensity, and cost of services can thus be explained by the difference in their latent class membership. Each latent class, therefore, exhibits a distinct class-specific profile based on the mix of observed superutilization indicators. More formally, the classification approach models the probability, P, of the latent class membership, c, of each child, given the type of utilization pattern experienced by those children, y.

(1) $$P(L = c \mid Y = y)$$

The observed response pattern in our context is the presence or absence of superutilization for a given child on a given measure. The analysis enables us to explain the differences in superutilization patterns with a sufficient number of latent classes in both the Tennessee and Florida samples.

The general process used to arrive at our final latent class models is described briefly below. First, for both the Tennessee and Florida samples, we estimated a number of latent class models ranging from a one-class to a ten-class model. For each model, we assessed performance using several types of diagnostic statistics, such as information criteria including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the sample-size adjusted measures of the AIC and BIC, and different variants of likelihood ratio tests comparing nested models[11]. In addition, we also examined the entropy coefficient for each model, which measures the degree of homogeneity within each class, and the cross-classification error of the latent classes, which is the primary measure of class assignment accuracy.

Ultimately, our final decision regarding the most appropriate latent class model for the Tennessee and Florida samples was based on the need to optimize across a number of statistical

[10] The probabilistic assignment to a latent class is in contrast to more traditional cluster analysis approaches that group observations into homogenous classes by minimizing a distance function between observations. In these approaches, however, group assignment is performed deterministically -- usually based on a minimization criterion. The probabilistic nature of latent class modeling and its compatibility with a wide array of diagnostic testing procedures to assess model fit and classification accuracy are key advantages of this approach over cluster analysis approaches. It should also be noted that cluster analysis is more appropriate for continuous variables, where distance from a centroid is spatially meaningful. In this case, our variables are coded dichotomously, which limits their suitability for more traditional cluster analysis techniques. Moreover, latent class techniques, which we believe are statistically preferable to cluster analysis, are not generally appropriate for continuous variables. Thus, we preferred to examine types of superutilization using categorically coded variables and more suilatent class techniques.

[11] These measures include the Vuong-Lo-Mendell-Rubin likelihood ratio test, the Lo-Mendell-Rubin adjusted likelihood ratio test, and the parametric bootstrapped likelihood ratio test.

and substantive criteria. Specifically, we considered a combination of factors including model fit (that is, minimizing the AIC and BIC), high entropy (values above 0.80), minimal cross-classification error, parsimony (preference for fewer classes when improvement in model fit is small), and, perhaps most importantly, substantive interpretability based on subject matter expertise and policy-relevance. We discuss each of these criteria in depth in Appendix D. An additional point to note is that, because this is a descriptive exploratory analysis, we did not explicitly include covariates in the modeling process. Although including covariates in a latent class model can improve classification accuracy, the degree of improvement is largely a function of the predictive effect size of the covariate, with higher effect sizes leading to better predictive performance. The caveat, however, is that the selection of covariates should be grounded in theory and should exhibit clear differentiation across latent classes (Wurpts and Geiser, 2014). However, given the exploratory nature of this study, we did not have strong theoretical expectations regarding potential candidate covariates. Moreover, one key demographic variable that is often important in child welfare research—namely, age—was used to adjust measures that are part of the latent class analysis, which makes it inappropriate for use as a covariate. Furthermore, there is no clear apriori reason to expect other candidate variables such as gender or race/ethnicity to clearly differentiate across latent classes of superutilizers. As such, we opted for a simpler approach that only used the superutilization measures themselves in the LCA.

However, we were still interested in profiling the final latent classes using additional information that was available. Thus, rather than explicitly including covariates, the alternative approach we adopted was to examine the distribution of various contextual variables from the administrative data set across the latent classes after we finalized our results. This profiling approach is consistent with approaches often used for descriptive LCA (Vermunt 2010).

All latent class models were estimated using MPlus software version 7 using the TYPE= MIXTURE command, which applies robust maximum likelihood estimation (Muthén 2010). To automate the MPlus analysis and help manage the data, we also used the MplusAutomation package in R (Hallquist and Wiley 2011). We provide details on our approach to model estimation, model selection, and programming in Appendix D.

C. Types of superutilization

In this section, we present the latent class results for the Tennessee and Florida samples. We first describe the general latent class results for each site. After providing a general overview of the results, we highlight the defining characteristics of each latent class. In addition, we also summarize a few key definitional characteristics and other characteristics based on the demographics, assessments, investigations, and other data available for the Tennessee and Florida samples. This information provides more context for interpretation. See Appendix D for full descriptive results showing the distributions of characteristics for the final latent class models.

1. Tennessee

For Tennessee, we determined that a seven-class model was the most appropriate for describing the types of superutilization derived from the data (discussed further in Appendix D). VII.1 provides a summary of the posterior (model-based) response probabilities for the children in the superutilizer sample conditional on their latent class membership. These conditional probabilities describe the probability of being flagged as a superutilizer (that is, having a value of 1 versus 0) on a particular measure of superutilization given membership in a particular latent class. These probabilities can be interpreted in a way that is analogous to factor loadings in factor analysis. Specifically, probabilities close to 0 or 1 indicate that the measure discriminates well across latent classes and provides clearer differentiation. For example, within a given class, a probability close to 1 on a measure means that children in that class are highly likely to experience superutilization for that measure. Conversely, a probability closer to 0 indicates that children are much less likely to experience superutilization on that measure. Probabilities closer to 0.5 indicate more moderate discrimination and greater uncertainty regarding whether children in a class are likely to experience superutilization for that measure. It should be noted, however, that more moderate (as opposed to clear) differentiation is not problematic from an analytical perspective. Moderate discrimination is ultimately a function of the data and the model and is still useful for descriptive purposes.

VII.1. Tennessee latent class membership probabilities

	Latent class (% of sample)						
	Class 1 (23.0%)	Class 2 (12.2%)	Class 3 (21.5%)	Class 4 (7.3%)	Class 5 (9.1%)	Class 6 (8.6%)	Class 7 (18.1%)
Measure of superutilization[a]	Latent class membership probabilities.						
Total number of placement moves	1.000	0.000	0.081	0.000	0.017	0.078	0.122
Total number of foster care episodes	0.505	1.000	0.055	0.000	0.040	0.021	0.069
Total episodes length of stay	0.425	0.251	0.034	1.000	0.000	0.000	0.085
Average share of time in group/congregate care	0.095	0.014	0.067	0.042	0.051	0.000	0.522
Child welfares services per year	0.003	0.004	0.879	0.000	0.003	0.025	0.022
Medicaid inpatient per year	0.114	0.036	0.059	0.050	0.039	0.049	0.245
Medicaid outpatient per year	0.105	0.124	0.087	0.007	1.000	0.000	0.166
Medicaid emergency per year	0.078	0.066	0.119	0.024	0.134	1.000	0.153
Child welfare service cost per year	0.011	0.008	0.614	0.001	0.014	0.004	0.039
Total placement cost per year	0.203	0.109	0.044	0.025	0.032	0.000	0.683

Source: Tennessee DCS; TennCare.

Note: The Tennessee superutilizer sample includes 12,332 children.

[a] This table shows the probability of class membership conditional on being a superutilizer for a given measure (that is, when a measure equals 1 vs. 0). In several cases, the value of the predicted probability is equal to 1.000 or 0.000; this occurs when there is lack of variation in the measure for a given latent class.

To provide a more intuitive interpretation, we show the same aggregated predicted class membership probabilities in Figure VII.1 and label each of the seven classes based on the key superutilization characteristics that most differentiate each one. Before summarizing the defining features of each class, we first explain how to read the figure. The y-axis of the figure shows the probability from zero to one that the members of a given class experience superutilization for a given measure. The headers for each graph are our shorthand labels for each class based on the highest predicted probabilities on the measures that most differentiate each class. As noted above, although a probability close to zero is a sharp differentiator between classes, and can also be used for interpretation, we chose to focus on the higher predicted probabilities in labeling the classes because we believe the presence of a characteristic (as opposed to its absence) provides a more intuitive interpretation. To the right of the table, we include a color-coded key with each color corresponding to a specific measure of superutilization. Visually, the measures with highest probabilities in the figure are those that define the class.

Figure VII.1. Tennessee latent class probabilities by superutilization measure

Drawing on the results presented in VII.1 and Figure VII.1, as well as the descriptive analysis results of characteristics depicted in Tables D.7 through D.25 in Appendix D, we next summarize the distinguishing features of each class. For each, we first note the key superutilization characteristics, based primarily on higher predicted probabilities that distinguishes it from other classes and then briefly summarize key characteristics that help describe the class. Figure VII.2 provides a summary of key distinguishing features for each class in Tennessee.

Figure VII.2. Percent of Tennessee sample among types of superutilization and their distinguishing characteristics

1. Foster Care Placement Instability
N=2,841 (23.0%)

- High number of placement moves (54.7% had 7 or more)
- Reason for removal: neglect (42.6%), parent drug use (39.1%), physical abuse[A] (14.8%), caretaker inability to cope[A] (11.3%)
- Most had a prior child welfare investigation (58.4%)
- 62.0% exited custody, among those 48.1% reunified, 23.8% adopted

4. Long Duration in Foster Care
N=906 (7.3%)

- 97.1% of out-of-home custody spent in family foster care[A]
- Reason for removal: parental drug abuse[A] (55.4%)
- Nearly all (96.9%) received child welfare services: clothing assistance (71.1%), legal services[A] (63.8%), and documentation services[A] (55.6%)
- Lowest percentage of children receiving Medicaid services (65.2%)[B]
- 40.7% are younger than 1 year old[A]
- 64.2% exited custody, among those 80.2% were adopted[A]

2. Multiple Foster Care Episodes
N=1,505 (12.2%)

- High percent with prior custody episodes[A] (63.3%)
- 75% had a prior child welfare investigation[A]
- Adolescents (47.5%), female[A] (52.4%)
- Reasons for removal: neglect[A] (46.2%), child behavior problem[A] (24.9%), abandonment[A] (19.0%), incarceration of parent[A] (11.1%), caretaker inability to cope[A] (11.4%), sexual abuse[A] (7.4%), relinquishment[A] (4.1%), death of parent[A] (1.7%)

5. Medicaid Outpatient Service Use
N=1,126 (9.1%)

- Highest percent (100%) with Medicaid outpatient services with a per-child average of 68.4 services[A]
- 91.6% received behavioral health outpatient services[A]
- Lowest percent (70.9%) of children receiving child welfare services[B]
- 75.2% exited custody[A], among those 58.4% reunified[A]

3. Child Welfare Service Use
N=2,655 (21.5%)

- All received child welfare services: clothing assistance (71.5%), substance abuse testing/treatment[A] (44.9%), supervised visitation[A] (37.7%), assessments[A] (34.5%), family or parenting support services[A] (32.4%), therapy/counseling services[A] (30.9%)
- 64.9% exited custody, among those 48.7% reunified, 29% relative/kinship placement[A]

6. Medicaid Emergency Service Use
N=1,069 (8.7%)

- Highest percent (100%) with Medicaid emergency services with a per-child average of 7.0 services[A]
- High percent (82.2%) received child welfare services: clothing assistance[A] (78.8%), substance abuse testing and treatment (24.3%)
- 37.8% ages 1 to 5 years[A]
- Lowest percent (29.2%) with a prior child investigation[B]

7. Use of Group/Congregate Care and Placement Costs N=2,230 (18.1%)

- High average share of time (48.1%) spent in group/congregate care among all time in out-of-home custody was 48.1 percent[A]
- Adolescents[A] (61.3%), male[A] (58.2%)
- Reasons for removal: behavioral problems (41.1%)[A]
- 61.9% exited custody, among those 47.1% reunified, 23.5% emanicipated[A]

[A] Indicates highest proportion of this characteristic across all latent classes.

[B] Indicates lowest proportion of this characteristic across all latent classes.

Class 1: Foster care placement instability (2,841 children, which is 23.0 percent of the sample). The defining superutilization characteristic of Class 1 is the high number of foster care placement moves experienced by children in this class. Specifically, all children in this class experience superutilization on the number of foster care placement moves (predicted probability = 1). Also, children in this class may also experience moderately higher numbers of custody episodes (predicted probability = 0.502) and longer lengths of stay per custody episode (predicted probability = 0.425).

When looking at the descriptive analysis results of service use for these defining characteristics among those in Class 1, we find the following:

- 54.7 percent of children in this class had 7 or more placement moves across all out-of-home custody episodes, with an average of 8.2 placement moves.
- 34.7 percent had prior out-of-home child welfare custody episodes.
- 92.0 percent of those in the class received child welfare services, with an average of 7 services. Among children in Class 1 who received child welfare services, the most common services were clothing assistance (71.4 percent), other services (41.8 percent), substance abuse testing and treatment (28.9 percent), and family and parenting support services (22.8 percent).
- 87.8 percent of those in Class 1 received Medicaid physical and behavioral health services.

Other characteristics and child welfare outcomes of this class include:

- 30.9 percent of children in Class 1 are between 1 and 5 years old; 53.5 percent of children are male, the second highest proportion of male children across all Tennessee latent classes.
- For 42.6 percent of the children in Class 1, neglect was listed as the reason for removal; this is the second highest proportion across all seven latent classes. For 39.1 percent, parent drug abuse was named as a reason for removal. In addition, 14.8 percent of those in Class 1 had physical abuse as a reason for removal, which was the highest proportion across all classes. Also, 11.3 percent of those in Class 1 had caretaker inability to cope as a reason for removal, one of the highest proportions across the seven classes.
- 58.4 percent of children in this class had a prior child welfare investigation, the second highest proportion for this measure among all the classes.
- 62.0 percent of children in Class 1 exited custody; almost half (48.1 percent) were reunified and 23.8 percent were adopted.

Class 2: Multiple foster care episodes (1,505 children, which is 12.2 percent of the sample). All children in Class 2 experience superutilization with respect to multiple out-of-home custody episodes (predicted probability = 1). Interestingly, this class is also characterized by the very low probability of experiencing superutilization based on the number of placement moves (in contrast to Class 1). This suggests that children who experience a relatively high number of recurring spells in foster care may not necessarily be the same children who experience a high number placement moves within those spells.

Key descriptive analysis results of the defining service use characteristics among those in Class 2 include the following:

- 63.3 percent of the children in Class 2 had prior custody episodes before the study window, nearly twice the proportion of the next highest class on this measure.
- In addition, 75.0 percent of children had a prior child welfare investigation, the highest proportion across all classes.
- In regard to placement moves, children in this class had 4.4 placement moves across all custody episodes.
- 85.4 percent of children in Class 2 received child welfare services, with an average of six services. Among those children who received services, the services with the highest proportion included clothing assistance (74.8 percent), other services (30.0 percent), substance abuse treatment and testing services (26.3 percent), and family or parenting support services (25.7 percent).
- 89.5 percent of children in Class 2 received Medicaid services.

Other distinguishing characteristics and child welfare outcomes among those in Class 2 include:

- Almost half (47.5 percent) of children in Class 2 are adolescents, between 13 and 17 years old; 52.4 percent of children in Class 2 are female, the highest proportion of females across all Tennessee latent classes.
- Among those in Class 2, 46.2 percent of children had neglect, 24.9 percent had child's behavior problem, 19.0 percent had abandonment, 11.1 percent had incarceration of parents, 11.4 percent had caretaker inability to cope, 7.4 percent had sexual abuse, 4.1 percent had relinquishment, and 1.7 percent had death of parents as reasons for removal. For each of these reasons, the proportion for Class 2 represents the highest proportion for those reasons across all classes.
- Overall, 67.0 percent of children exited custody. Reunification accounted for the greatest percentage (46.0 percent); however, 18.0 percent, or almost 1 in 5 children, exited due to emancipation, the second highest percentage among all Tennessee classes.

Class 3: Child welfare service use (2,655 children, which is 21.5 percent of the sample). Children in Class 3 experience a high level of child welfare service utilization (the annualized rate of services per year). The probability of being flagged for superutilization for child welfare services is the highest in this group compared to any of the other classes (predicted probability = 0.879). Similarly, the incurred cost per year of child welfare services is also higher for this group than for other classes (predicted probability = 0.614). Thus, children in Class 3 are more likely to experience superutilization on two separate but related dimensions—namely, service receipt and service cost.

The descriptive analysis results for the defining characteristics regarding services use among those in Class 3, include the following:

- Only 4.4 percent of children in Class 3 had prior out-of-home custody episodes.
- In regard to number of foster care placements, children in the class had an average of 2.3 placement moves across all custody episodes.
- All children (100 percent) received child welfare services, with an average of 11 services, which is the highest average among all the classes in Tennessee. Among those receiving child welfare services in Class 3, the most common types included clothing assistance (71.5 percent), substance abuse and testing services (44.9 percent), supervised visitation (37.7 percent), assessments (34.5 percent), family or parenting support services (32.4 percent), and therapy or counseling services (30.9 percent). With the exception of clothing assistance, each of the proportions for Class 3 is the highest for each type of service compared to all other latent classes in Tennessee.
- 85.2 percent of children in Class 3 received Medicaid services.

Other characteristics and child welfare outcomes among those in Class 3 are summarized below:

- 28.8 percent of children in Class 3 are between ages 1 and 5 years; however, the proportion of children in each age category is the most evenly distributed in this class. Overall, 50.6 percent of children in Class 3 are female.
- The most commonly reported reasons for removal among the children in this class included parental drug abuse (42.9 percent), which is the second highest proportion across all classes in Tennessee, and neglect (38.5 percent).
- 34.0 percent of children in this class had a prior investigation.
- 64.9 percent of children in Class 3 exited custody. The permanency types with the highest proportion included reunification (48.7 percent) and relative or kinship placement (29.0 percent); the latter is the highest proportion among all Tennessee classes.

Class 4: Duration in foster care (906 children, which is 7.3 percent of the sample). Children in Class 4 are distinguished from the other classes based primarily on their long stays in out-of-home custody. Although children in this class have low probabilities of experiencing superutilization on the other nine measures, they all experience superutilization in terms of length of stay in foster care (predicted probability = 1).

Key findings regarding defining service use characteristics among those in Class 4 include the following:

- Very few children in Class 4, only 0.7 percent, had a prior out-of-home custody episode.
- In regard to foster care placements, on average, children in Class 4 had 2.5 placement moves across all custody episodes. Children in Class 4 also had the highest percentage (97.1 percent) across all classes in regard to the average share of time spent in family foster care during their time in out-of-home custody.
- 96.9 percent of children in Class 4 received child welfare services, with an average of eight services. Among those receiving services, the most frequently used services include clothing

assistance (71.1 percent), legal services (63.8 percent), and documentation services (55.6 percent), which are the highest proportion for those services except for clothing assistance among the classes. In addition, 32.7 percent received substance abuse testing and treatment services, which is the second highest among all classes.

- Only 65.2 percent of children in Class 4 received Medicaid services, which is the lowest among all the classes in Tennessee.

Other characteristics to note regarding Class 4 include the following:

- Children in Class 4 are largely younger, with 40.7 percent of children younger than 1 year old, the highest proportion of young children among all Tennessee classes. 50.3 percent of children in this class are female.
- Over half (54.4 percent) of the children in Class 4 had parental drug abuse as a reason for removal, the highest proportion across all classes in Tennessee,
- 35.7 percent of children in Class 4 had a prior child welfare investigation.
- 64.2 percent of children in Class 4 exited child welfare custody within the study window. Among those who exited, 80.2 percent exited to adoption, which is higher than any other class.

Class 5: Medicaid outpatient service use (1,126 children, which is 9.1 percent of the sample). Children in Class 5 are distinguished from the other classes based on their utilization of Medicaid outpatient health services. In fact, all children in this class experience superutilization of outpatient health services (predicted probability = 1) but are highly unlikely to experience superutilization on any other measure (predicted probabilities are close to 0 for most measures).

The descriptive analysis results for the defining characteristics regarding service use among those in Class 5 include the following:

- Few children (0.1 percent) in Class 5 had prior out-of-home custody episodes.
- Children in Class 5 had an average of 2.7 placement moves across all custody episodes. They also had the second highest average for share of time in custody spent in group or congregate care (13.8 percent).
- 70.9 percent of children in Class 5 received child welfare services, which was the lowest proportion across all classes in Tennessee. The most common types of services among those in Class 5 include clothing assistance (69.9 percent), substance abuse testing and treatment (24.1 percent), other services (20.3 percent), and family or parenting support services (20.1 percent).
- As the primary defining characteristic, 100 percent of children in Class 5 received Medicaid service, with 100 percent receiving outpatient services. Also, the per-child average number of outpatient services received is 68.4, which is the highest among all classes in Tennessee. Moreover, among children receiving outpatient services, 91.6 percent received behavioral health outpatient services, which is higher than any other class.

Other distinguishing characteristics and child welfare outcomes among those in Class 5 include:

- Over half (52.2 percent) of children in Class 5 are between 13 and 17 years old, which is the second highest proportion of older children across all classes; 50.9 percent of children are female.
- In regard to reason for removal, the most common reasons include neglect (34.2 percent), child's behavioral problem (24.6 percent) and parental drug abuse (24.2 percent).
- Over half (51.8 percent) of children in Class 5 had a prior investigation.
- 75.2 percent of children in Class 5 exited custody, which is the highest among all classes in Tennessee. Additionally, among those who exited, reunification was the most common permanency type (58.4 percent), the highest among all classes in Tennessee.

Class 6: Medicaid emergency service use (1,069 children, which is 8.7 percent of the sample). Children in Class 6 are characterized by their high use of Medicaid emergency behavioral and physical health services. All children in this class are identified as experiencing superutilization on the emergency health measure (predicted probability = 1). Children in Class 6 are also characterized by having a very low probability of experiencing superutilization on any of the other nine measures.

The descriptive analysis results for the defining characteristics regarding service use among those in Class 6 include the following:

- Few children (0.1 percent) in Class 6 had prior out-of-home custody episodes.
- In regard to foster care placement moves, children in Class 6 had an average of 2.6 placement moves across all custody episodes. Also, those in Class 6 had very low shares of time in group or congregate care among their time in custody, with an average of 0.8 percent.
- 82.2 percent of children in Class 6 received child welfare services. The most commonly used services among children in Class 6 include clothing assistance (78.8 percent), which was the highest percentage across all classes in Tennessee, substance abuse testing and treatment (24.3 percent), other services (20.6 percent), and therapy or counseling services (18.0 percent).
- In regard to the defining characteristic of Medicaid services, 100 percent of children in Class 6 received Medicaid services, with 100 percent receiving emergency services and 99.6 percent receiving outpatient services. The per-child average number of emergency health services is 7.0, which is higher than any other class.

Other key characteristics and child welfare outcomes among those in Class 6 include:

- Children in class 6 are generally younger, with 37.8 percent of the children between ages 1 and 5 years, which is the highest proportion in this age category across all other classes, and 27.5 percent less than 1 year old. Females make up 51.9 percent of the children in Class 6.

- The most commonly reported reasons for removal include parental drug use (41.2 percent) and neglect (39.3 percent).
- 29.2 percent of children had a prior child investigation, the lowest proportion across all classes.
- 74.1 percent of children in Class 6 exited custody, which is the second highest proportion among all classes. Among those who exited, 55.7 percent achieved reunification, which is the second highest proportion across all classes. 27.3 percent exited custody to a relative or kinship placement.

Class 7: Use of group/congregate care placements and placement costs (2,230 children, which is 18.1 percent of the sample). Children in Class 7 have the highest probability of experiencing superutilization in terms of the share of time in out-of-home placements spent in group home or congregate care (e.g., shelter care, residential treatment). Although the predicted probability of superutilization on this measure is moderate (predicted probability = 0.522), it is the highest across all classes examined for the Tennessee sample. Similarly, children in Class 7 also have a higher probability of experiencing superutilization related to higher placement costs compared to other classes (predicted probability = 0.683).

The descriptive analysis results for the defining characteristics regarding service use among those in Class 7 include the following:

- 3.0 percent of children in Class 7 had prior out-of-home custody episodes.
- On average, children in Class 7 had 4.1 foster care placement moves.
- For children in Class 7, the average share of time spent in group or congregate care among all time in out-of-home custody was 48.1 percent. This proportion is significantly higher than for any other class in Tennessee.
- 81.4 percent of children in Class 7 received child welfare services, with the most commonly used services being clothing assistance (58.4 percent), other services (40.6 percent), transit assistance (22.7 percent), and assessments (20.0 percent).
- 89.3 percent of children in Class 7 received Medicaid services.

Other characteristics and child welfare outcomes among those in Class 7 include:

- Most (61.3 percent) of the children in Class 7 are adolescents between the ages of 13 and 17, which is the highest proportion of older children for any of the classes for Tennessee. Also, 58.2 percent of the children are male, making this class the most predominantly male of all classes examined.
- The most common reasons for removal among children in Class 7 include behavioral problems (41.1 percent), which is the highest proportion across all classes.
- Children in Class 7 had higher percentages with higher levels of CANS scores compared to other classes.
- 47.9 percent of children had a prior child welfare investigation.

- 61.9 percent of the children in Class 7 exited custody. Of those who exited, the most common permanency type was reunification (47.1 percent); however, 23.5 percent exited due to emancipation, the highest proportion of children with this exit type across all classes.

2. Florida

For the Florida sample, we determined that an eight-class model was the most appropriate for describing the types of superutilization. Similar to the structure in the previous section, both VII.2 and Figure VII.2, below, provide the summary of the posterior response probabilities for the children in the Florida superutilization sample conditional on their latent class membership.

VII.2. Florida latent class membership probabilities

	Latent class (% of sample)							
	Class 1 (14.0%)	Class 2 (5.4%)	Class 3 (23.2%)	Class 4 (10.2%)	Class 5 (19.9%)	Class 6 (5.6%)	Class 7 (8.8%)	Class 8 (12.8%)
Measure of superutilization[a]	Latent class membership probabilities.							
Total number of episodes	0.054	0.492	0.026	0.000	1.000	0.000	0.000	0.024
Out-of-home episode length of stay	0.063	0.524	0.000	0.163	0.432	1.000	0.000	0.036
Child welfare CBC-purchased service cost per year	0.672	0.570	0.034	0.000	0.033	0.021	0.056	0.000
Chlid welfare CBC-purchased services per year	0.802	0.509	0.025	0.030	0.012	0.035	0.000	0.012
Medicaid emergency per year	0.077	0.239	0.191	0.017	0.040	0.000	0.087	1.000
Medicaid inpatient per year	0.059	0.401	0.182	0.088	0.015	0.044	0.000	0.063
Medicaid outpatient per year	0.122	0.347	0.509	0.000	0.113	0.014	0.144	0.000
Mental health services per year	0.100	0.383	0.334	0.018	0.110	0.019	0.010	0.005
Average share of time in group home/residential care	0.055	0.271	0.122	0.070	0.109	0.020	1.000	0.029
Substance abuse services per year	0.044	0.254	0.128	0.012	0.044	0.005	0.038	0.019
Total number of placement moves	0.126	0.825	0.065	1.000	0.475	0.000	0.053	0.089

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: The Florida superutilizer sample includes 3,726 children.

[a]This table shows the probability of class membership conditional on being a superutilizer for a given measure (that is, when a measure equals 1 vs. 0). In several cases, the value of the predicted probability is equal to 1.000 or 0.000; this occurs when there is lack of variation in the measure for a given latent class.

Figure VII.3. Florida latent class probabilities by superutilization measure

The results of the descriptive analysis of characteristics for each class in our Florida sample are depicted in Tables D.26 through D.44 in Appendix D. Figure VII.4 provides a summary of key distinguishing features for each class. Below, we describe key highlights for each of the eight latent classes and follow the same structure used to present the Tennessee findings.

Figure VII.4. Percent of Florida sample among types of superutilization and their distinguishing characteristics

1. Child Welfare Services Use
N=523 (14.0%)

- All received child welfare CBC-purchased services: assessments (21.8%), therapy/counseling (17.4%), caregiver/parent education[A] (3.8%)
- 54.1% male, 30.4% ages 1 to 5
- 49.9% exited custody, among those 50.6% reunified, 23.3% exited to guardianship

2. Complex Child Welfare and Medicaid Service Use N=201 (5.4%)

- High numbers of placement moves[A] (average of 18.4), Medicaid inpatient services[A] (average of 4.8), and Medicaid outpatient services* (average of 80.3)
- High percent receiving child welfare CBC-purchased services (86.8%), among those 43.3% received 3 or more services[A]
- High percent ages 6 to 12 (34.3%) and 13 to 17[A] (37.8%)

3. Modest Medicaid Service Use
N=865 (23.2%)

- 98.2% received Medicaid outpatient services, 33.2% received Medicaid inpatient services
- Half (50.6%) received substance abuse and mental health services
- 58.8% had a prior child welfare investigation
- Only 12.7% received child welfare services

4. Foster Care Placement Instability
N=381 (10.2%)

- High number of foster care placement moves (average of 6.4)
- Lowest percent with prior child welfare investigation (27.0%) or prior custodial episodes (3.9%)[B]
- Only 3.1% received substance abuse and mental health services[B]
- Over half (59.6%) are younger than 1 year old[A]
- 55.4% exited custody[A], among those 64.9% reunified and 27.5% were adopted

5. Multiple Foster Care Episodes
N=741 (19.9%)

- 58.3% had prior out-of-home custody episodes[A]
- 47.4% are ages 6 to 12[A]
- High average number of placement moves (7.9)
- 82.9% had a prior child welfare investigation[A]

6. Duration in Foster Care
N=210 (5.6%)

- 92.4% of out-of-home custody spent in family foster care[A]
- 43.8% are younger than 1 year old, 54.8% female[A]
- Only 27.1% exited custody[B], of those 57.9% were adopted[A]

7. Use of Group/Residential Care Placements N=327 (8.8%)

- 46.9% of out-of-home custody spent in group home/ residential placement[A]
- Only 4.0% had prior out-of-home custody episodes
- Few (9.8 %) received child welfare CBC-purchased services, of those many received assessment services (43.8%)[A]
- 40.1% ages 6 to 12 years, 57.8% male[A]
- 41.3% exited custody, of those 88.1% reunified[A]

8. Medicaid Emergency Services Use
N=478 (12.8%)

- All received Medicaid emergency services[A], with an average of 5 emergency services
- 99.4% received Medicaid outpatient services[A]
- Few (6.1%) received child welfare CBC-purchased services[B]
- 40.2% ages 1 to 5[A]
- 39.1% exited custody, among those 70.1% reunified

Note: CBC means Community-Based Care agency, which is a human services organizations that Florida OCW contracts with to provide child and family social services.

[A] Indicates highest proportion of this characteristic across all latent classes.

[B] Indicates lowest proportion of this characteristic across all latent classes.

Class 1: Child welfare CBC-purchased service use (523 children, which is 14.0 percent of the sample). Children in Class 1 are distinguished primarily on the basis of their higher utilization of child welfare CBC-purchased services and service costs. Specifically, children in this class have relatively high probabilities of experiencing superutilization of services (predicted probability = 0.802) and incurring higher levels of costs per year (predicted probability = 0.672). By contrast, the children in Class 1 also exhibit very low probabilities of experiencing superutilization on any other measure. More broadly, this class appears to share similar defining characteristics to that of Class 3 from the Tennessee sample, which also has a high probability of superutilization on child welfare services and costs while similarly being unlikely to experience high utilization on other measures.

The descriptive analysis results of key defining characteristics of service for those in Class 1 include the following:

- Among the children in Class 1, 10.3 percent had prior out-of-home custody episodes.
- In regard to foster care placement moves, children in Class 1 had an average of 4.2 placement moves across all custody episodes.
- All children in Class 1 received at least one child welfare CBC-purchased service, which differentiates this class from all others in Florida, where the comparable percentage varies from 9.8 to 88.6. In terms of specific services, the more common services are assessments (21.8 percent) and other services (20.1 percent). Also, 17.4 percent of children in Class 1 received therapy/counseling, which is the second highest percentage across all classes, although this is the largest group in terms of actual numbers. In addition, 3.8 percent of children in Class 1 received caregiver/parenting education, which is the highest percentage across all classes.
- 95.6 percent of those in Class 1 received Medicaid services.
- 19.1 percent of children in Class 1 received other substance abuse and mental health services.

Other key descriptive characteristics of children in Class 1 include:

- In regard to demographics, 30.4 percent of children in Class 1 are between the ages of 1 and 5, and 29.1 percent are ages 6 through 12. Over half (54.1 percent) of the children in Class 1 are male.
- 53.9 percent of children in Class 1 had a prior child welfare investigation, which is in the middle of the distribution across all classes in Florida.
- Half (49.9 percent) of the children in Class 1 exited custody during the study window. Of those who exited, half (50.6 percent) achieved reunification and roughly a quarter (23.3 percent) exited custody to guardianship.

Class 2: Complex child welfare and Medicaid service use (201 children, which is 5.4 percent of the sample).

Children in Class 2 are distinguished from the other classes by exhibiting varied patterns of higher service use across a number of measures. Numerically, this is the smallest of the latent classes estimated for Florida as it includes only 201 children. In contrast to other classes, Class 2 shows high to moderate probabilities of experiencing superutilization across several measure dimensions. Children in this class, for example, have a high probability of experiencing a higher number of placement moves (predicted probability = 0.825). Similarly, children in this class also exhibit moderately higher probabilities of incurring higher child welfare CBC-purchased service costs (predicted probabilities = 0.570) as well as having longer durations in child welfare custody (predicted probability = 0.524), receiving more child welfare CBC-purchased services (predicted probability = 0.509), and having a higher number of foster care placements (predicted probability = 0.492). Children in this class also have more intermediate probabilities of experiencing superutilization for mental health services (predicted probability = 0.383) and inpatient Medicaid health services (predicted probability = 0.401). It should be noted that the probabilities of experiencing superutilization for these measures are generally lower than they are for others that distinguish key features of the classes. However, the probabilities are still consistently higher than they are for other classes. Thus, we consider this pattern to be consistent with the idea of complex utilization patterns more broadly.

When looking at the descriptive analysis results for the defining characteristics of service use among those in Class 2, we find the following:

- Over half (55.2 percent) had a prior custody episode, the second highest percentage across all classes.
- Children in Class 2 had an average of 18.4 placement moves across all episodes; this is much higher than all other classes in Florida, which had averages from 2.9 to 7.9 placement moves.
- In regard to type of foster care, children in Class 2 had an average share of time in group homes or residential treatment placements of 19.2 percent among all their time in out-of-home placements, which was the second highest among the Florida classes.
- With respect to child welfare services, 86.8 percent of children in Class 2 received at least one child welfare CBC-purchased service, which was the second highest among the classes. Moreover, 43.3 percent of children in Class 2 had three or more child welfare CBC-purchased services, which is the highest proportion across all classes in Florida. The more commonly reported services include assessments (39.3 percent), other services (26.4 percent), and therapy or counseling (19.7 percent); the last was the highest among all classes in Florida.
- 97.5 percent of children in Class 2 received Medicaid services, with an average number of 4.8 inpatient services and 80.3 outpatient services, which were the highest averages among all the classes.
- Overall, 62.2 percent of children in Class 2 received other substance abuse and mental health services, which is the highest proportion across all classes.

Other key descriptive characteristics among those in Class 2 include:

- Children in Class 2 tend to be older, with 34.3 percent between the ages of 6 to 12 and 37.8 percent between the ages of 13 and 17; the latter is the highest proportion of children in this age category among all classes. Overall, 56.2 percent of the children are male, which is the second highest proportion of male children across all classes in Florida.
- 77.1 percent of the children in this class had a prior child investigation, which is the second highest proportion across all classes.
- 42.3 percent of the children in Class 2 exited custody. Of those who exited, the most common permanency types were reunification (45.9 percent) and adoption (29.4 percent).

Class 3: Medicaid and mental health service use (865 children, which is 23.2 percent of the sample). Children in Class 3 are generally unlikely to experience superutilization on child welfare service measures. However, this class has a slightly higher probability of experiencing superutilization of Medicaid outpatient services (predicted probability = 0.509) compared to the other classes identified for Florida. Class 3 also has the second highest probability of experiencing superutilization for mental health services (predicted probability = 0.334).

Key defining characteristics of service use among those in Class 3 include the following:

- 10.8 percent of children in Class 3 had a prior out-of-home custody episode.
- In regard to placement moves, those in Class 3 had an average of 4.2 foster care placement moves.
- With regard to type of foster care placement, the average share of time spent in group homes or residential treatment among all time in out-of-home placement was 11.3 percent.
- 12.7 percent of children in Class 3 received child welfare CBC-purchased services, which is the third lowest among the Florida classes. The most common services include documentation services (23.6 percent), such as transcript services, certified copies of legal and medical documents, and videographer services, assessments (21.8 percent), and other services (18.2 percent).
- 98.4 percent of those in Class 3 received Medicaid services, with 98.2 percent receiving outpatient services and 33.2 percent received inpatient Medicaid services, both of which are the second highest among the Florida classes. On average, those in Class 3 received 38.8 outpatient services and 3.6 inpatient services; both were the second highest averages across the Florida classes.
- Half (50.6 percent) of the children in this class received some form of substance abuse and mental health service, which is the second highest proportion across all classes. More specifically, of the children receiving these services, 45.7 percent of these children received mental health services, which was the second highest across all classes.

Other characteristics and child welfare outcomes among those in Class 3 include:

- In regard to demographic characteristics, 36.4 percent of children in Class 3 are between ages 6 and 12; 51.1 percent of children are male.
- 58.8 percent of children had a prior child welfare investigation.

- 52.7 percent of the children in Class 3 exited custody, which is the second highest among all classes. Among those who exited, the most common permanency type was reunification (69.3 percent), followed by guardianship (17.1 percent).

Class 4: Foster care placement instability (381 children, which is 10.2 percent of the sample). Children in Class 4 are distinguished from those in other classes by the high number of foster care placement moves they experience. Specifically, all children in this class experience superutilization on this measure (predicted probability = 1). Children in this class are also highly unlikely to experience superutilization on any of the other 10 measures examined. This is also in contrast to Class 2, which, while experiencing a high number of placement moves, also exhibited higher utilization across multiple measures.

A summary of key defining characteristics of service use among those in Class 4 include the following:

- Only 3.9 percent had a prior custody episode, which is the lowest proportion across all classes.
- The average number of foster care placement moves across all episodes for children in Class 4 was 6.4. Although all children in this class experienced superutilization on the measure of placement moves, it should be noted that the average number of placement moves is actually the third highest across the classes. When defining Class 4, therefore, it is important to note that although all children in this class experience superutilization on this measure, this does not necessarily imply that these children have the highest absolute number of placement moves.
- 16.8 percent of children in Class 4 received child welfare CBC-purchased services, with the most common types including putative father registry (28.1 percent), which preserves the right to notice and consent of adoption of a child for unmarried biological fathers; family or caregiver services (26.6 percent), which was the highest percentage across all classes; and documentation services (25.0 percent).
- 86.1 percent of those in Class 4 received Medicaid services.
- Only 3.1 percent received substance use and mental health services, which was the lowest among all the Florida classes.

Other characteristics and child welfare outcomes among those in Class 4 include:

- In regard to demographic characteristics, children in Class 4 tend to be younger than other classes. Over half (59.6 percent) of children in Class 4 are younger than age 1 year, which is the highest proportion of children in the youngest age category across all classes, and 28.6 percent are between the ages of 1 and 5. Over half (52.5 percent) of children are male.
- 27.0 percent of children had a prior child welfare investigation, which is the lowest proportion across all classes.
- 55.4 percent of the children in Class 4 exited custody, which is the highest among all classes. Among those who exited, the most common permanency type was reunification (64.9 percent) followed by adoption (27.5 percent).

Class 5: Multiple foster care episodes (741 children, which is 19.9 percent of the sample). Children in Class 5 are differentiated based on multiple out-of-home custody episodes. All children in this class experience superutilization with respect to the number of custody episodes (predicted probability = 1). Children in Class 5 also have more moderate probabilities of experiencing superutilization on two related measures—namely, placement moves (predicted probability = 0.475) and duration in out-of-home care (predicted probability = 0.432).

A summary of key defining characteristics of service use among those in Class 5 includes the following:

- Over half (58.3) percent had a prior custody episode, which is the highest among all classes on this measure.
- On average, children in Class 5 had 7.9 foster care placement moves, which is the second highest among the classes for Florida.
- Children in Class 5 spent in an average of 64.8 percent of their time in family foster care during their total time in out-of-home placements.
- 16.9 percent of children in Class 5 received child welfare CBC-purchased services. Among those receiving child welfare services, the most common services are assessments (21.6 percent), documentation services (18.4 percent), and family or caregiver support services (15.2 percent).
- 93.1 percent of children in Class 5 received Medicaid services.
- About a quarter (25.9 percent) of children in Class 5 received other substance use and mental health services.

Other characteristics and child welfare outcomes among those in Class 5 include:

- In regard to demographic characteristics, 47.4 percent of children in Class 5 are between 6 and 12 years old, which is the highest proportion in this age group across all classes in Florida. 56.0 percent of the children are male, which is the second highest proportion of males across the classes.
- 82.9 percent of children had a prior child welfare investigation, which is the highest among all classes on this measure.
- 45.6 percent of children in Class 5 exited custody. Among those who exited, 61.8 were reunified and 21.6 percent achieved guardianship.

Class 6: Duration in foster care (210 children, which is 5.6 percent of the sample). The distinguishing feature of children in Class 6 is their experience with relatively long durations in out-of-home child welfare custody episodes. Although these children are very unlikely to have high levels of utilization on any of the other 10 measures examined for Florida, they all experienced superutilization on the length of time spent in out-of-home child welfare custody (predicted probability = 1).

A summary of key defining characteristics of service use among those in Class 6 include the following:

- 9.5 percent of those in Class 6 had prior out-of-home child welfare custody episodes.
- The average percentage of time spent in family foster care while in out-of-home custody was 92.4 percent for children in Class 6. This is the highest percentage among any classes in Florida.
- 32.4 percent of the children in Class 6 received child welfare CBC-purchased service, with the most common services being putative father registry (42.6 percent) and documentation services (25.0 percent).
- 91.0 percent of children in Class 6 received Medicaid services.
- 5.2 percent of children in Class 6 received other mental health or substance abuse services.

Other characteristics and child welfare outcomes among those in Class 6 include:

- 43.8 percent of children in Class 6 are younger than 1 year old. In addition, 54.8 percent of the children in the class are female, which is the highest proportion of females in any Florida class.
- 51.4 percent of children in this class had a prior child welfare investigation.
- 27.1 percent of the children in Class 6 exited custody, which is the lowest percentage of any class. Among those exiting, however, 57.9 percent were adopted, which is the highest proportion for this permanency type.

Class 7: Use of group/residential care placements (327 children, which is 8.8 percent of the sample). Children in Class 7 spent a high proportion of their time in out-of-home custody in group homes or residential treatment settings. Although these children are unlikely to have high utilization patterns on any of the other 10 measures we examined, they all experienced superutilization on the share of time spent in group homes (predicted probability = 1). The children in Class 7 have low probabilities of experiencing superutilization on any other measure.

A summary of key defining characteristics of service use among those in Class 7 include the following:

- Only 4.0 percent had a prior out-of-home child welfare custody episode, which is the second lowest across all classes.
- In regard to the defining characteristic, on average, children in this class spent 46.9 percent of their time in out-of-home custody in group or residential care. This is the highest percentage of time in group or residential care among all other classes.
- 9.8 percent of the children in Class 7 received any child welfare CBC-purchased services, which is the second lowest proportion across all classes. Among those who received child welfare CBC-purchased services, 43.8 percent received assessments, which is the highest proportion of all the Florida classes.
- 85.3 percent of those in Class 7 received Medicaid services.
- 14.1 percent of children in Class 7 received other mental health or substance abuse services.

Other characteristics and child welfare outcomes among those in Class 7 include:

- In regard to demographic characteristics, 40.1 percent of children in Class 7 are between 6 and 12 years old. 57.8 percent of children are male, which is the highest male proportion across all Florida classes.
- 54.7 percent of children in this class had a prior child welfare investigation
- 41.3 percent of children in Class 7 exited custody. Among those who exited, 88.1 percent had reunification indicated as the permanency type, which is the highest proportion across all Florida classes.

Class 8: Medicaid emergency services use (478 children, which is 12.8 percent of the sample). Children in Class 8 are distinguishable based on experiencing superutilization of Medicaid emergency behavioral and physical health services (predicted probability = 1). These children are also very unlikely to experience superutilization on any other measure we examined. In this respect, Florida Class 8 is very similar to Tennessee Class 6, which was also characterized by high utilization of Medicaid emergency services but was highly unlikely to experience superutilization on any other measure.

A summary of key defining characteristics of service use among those in Class 8 include the following:

- 6.7 percent of children in this class had a prior custody episode.
- In regard to the defining characteristics, children in Class 8 received an average of 5.0 emergency services, which is the second highest number across all classes.
- Children in Class 8 experienced an average of 2.9 placement moves, which was the lowest average among all the classes.
- Children in Class 8 spent an average of 76.9 percent of their time in family foster care among all of their time in out-of-home custody, which is the second highest among all the Florida classes.
- 6.1 percent of the children in Class 8 received child welfare services, which is the lowest percentage of any class. The most common services received among those in Class 8 included other services (27.6 percent), putative father registry (27.6 percent), and documentation services (24.1 percent).
- All children (100 percent) in Class 8 received Medicaid services, with 100 percent receiving emergency services and 99.4 percent receiving outpatient behavioral and physical health services, which are all highest among all the classes.
- 6.1 percent of the children in Class 8 received other substance abuse and mental health services.

Other characteristics and child welfare outcomes among those in Class 8 include:

- 40.2 percent of children in Class 8 are between 1 and 5 years old, which is the highest percentage in this age group across all classes. Children in class 8 are 52.9 percent male.

- A third (33.3 percent) of children in Class 8 had a prior child welfare investigation, which is the second lowest percentage across all classes.
- 39.1 percent of children in Class 8 exited custody. Among those who exited, 70.1 percent had reunification indicated as the permanency type, which is the second highest proportion across all classes.

D. Discussion and implications

The interpretation of the results and discussion of the implications have been informed by input from our site partners. Most importantly, given that we have identified meaningful differentiation of superutilization among seven classes for Tennessee and eight classes for Florida, the results emphasize the complex multidimensionality of superutilization. From a practice and policy perspective, this may require nuanced interventions for particular types of superutilization rather than a universal approach. A summary of other key findings and questions for implication that arose from discussing the LCA findings with site partners are provided in this section.

In particular, one latent class in each state includes children with many placement moves. Researchers and site partners raised questions regarding this group such as: What is causing the frequent placement moves? What actions could be taken to help address those factors, such as a change in the composition, sequencing or intensity of caseworker, behavioral health or other services? Are the children not receiving the appropriate type of services (such as attachment disorder or anger management counseling) necessary for them to heal from trauma? What underlying conditions need to be addressed better?

In Tennessee, there is a child welfare service class where children are receiving many child welfare services, but they also exit to reunification and kinship care at high rates among those that exit, the latter of which is highest among all classes. Does this mean that child welfare services are working and effective for these families? If more child welfare services were delivered to children in other classes, is it possible they would see greater rates of exits to reunification or kinship?

Also, a small but important group of children with a high number of emergency room visits is worth further investigation for each state. Questions arose among site partners including: While most of these visits relate to physical health needs, some are due to the need for emergency treatment for a behavioral health condition, but which conditions and what could have been done to prevent it? Are these children experiencing a higher rate of serious physical injuries? Are a substantial portion of these visits for older children due to suicide ideation or a suicide attempt? Are a substantial portion of these visits due to chronic health conditions? Do these children have a medical home that is being underutilized?

In Tennessee, there is a small but important group of "long-stayers" in foster care (41% are younger than 1 year old, 80% exit to adoption, and many of whom have parents challenged by substance abuse). The adoption rates are promising for this class in terms of achievement of permanency, but are there ways that the adoption process can be sped up so that children are not experiencing the longest durations in care and the overall time to adoption can be decreased? In Florida, there is a group of "long-stayers" in foster care who are more likely to be adopted than other superutilization groups in those three counties. For both states, are there any steps or aspects of the adoption process that could be improved to speed up that process? If a large group of these children are placed in treatment foster care, is there some special training and coaching that the foster parents might benefit from? Are there gaps in child functioning assessment that need to be addressed? Would geo-mapping where these children were placed from and their most recent placement location assist with any program refinements?

In both Tennesse and Florida, extensive use of group home and residential treatment is a superutilization class. The use of these forms of congregate care for children placed out-of-home has decreased in the United States by about 37% (U.S. Children's Bureau, 2016). Many states are focusing on ensuring that only children who truly need that service are placed in group care by closely examining assessment and other sources of data to identify distinctive groups of youth and what alternatives could be used for each.

Also, in Florida, one latent class is characterized by extensive use of both child welfare and Medicaid services. Further review of those cases might provide added information about what is working and not working for those youth, and if actions could have been taken early in that child's interaction with these service delivery systems that would lessen the need for these services in the long run. For example, did the child "fail up" into more restrictive and comprehensive services when a more targeted and timely set of services may have prevented that services trajectory?

Moreover, we identified classes or types of superutilization that shared similar distinguishing characteristics across both study sites, which may support a consistent type of superutilization found in numerous location. For example, we identified common types of superutilization where children in certain classes experienced high use of emergency services, long durations in child welfare custody, foster care placement instability, and multiple foster care episodes. It would be good to explore strategies for how to recognize youth who are on these trajectory early, and how that pathway direction could be altered early in the child's service interactions.

Research has shown that home- and community-based services for children previously residing in residential treatment facilities can improve school functioning and decrease the likelihood of substance abuse and ongoing child welfare involvement, and reduced costs (Urdapilleta et al., 2012). Yet, with some exceptions (Molitor et al., 2012; Trout et al, 2012), key post-permanency/post-reunification services are not well funded or provided – which leads to a 1 in 5 foster care reentry rate nationally (Roberts, O'Brien & Pecora, 2017). The results from this study show that Tennessee and Florida could build on this research, and possibly provide effective community and home-based services, while reducing system costs.

Health homes for children in foster care with chronic conditions, including behavioral and emotional disorders, can mediate the negative impacts of placement instability and lack of system coordination in meeting their needs (Allen & Hendricks, 2013).

Lastly, our results highlight the importance of considering service use in child welfare along with Medicaid services use and use of other services where available. Given we found several classes with combinations of service use among child welfare, health, and mental health and substance abuse services, policymakers and practitioners could benefit from understanding the complex service needs among these types of superutilization. At the very least, it underscores the value of using multiple data bases.

VIII. PREDICTORS OF SUPERUTILIZATION

A. Introduction

Up to this point, we have focused on the descriptive characteristics of children who experience superutilization. In particular, we have discussed different types of superutilization based on the results of the latent class analysis presented in the previous chapter. This chapter moves beyond these descriptive aspects to examine how well we can predict superutilization. The ability to predict superutilization may help child welfare agencies identify risk factors for high service usage before it occurs and enable program staff to create and target early interventions to help those children most at risk.

The primary goal of this chapter is to answer the following research question:

- What characteristics of children at the time of child welfare involvement—specifically at the time of entry into out-of-home care—predict superutilization?

To answer this question, we developed and estimated a predictive model using information that would be known to child welfare, Medicaid, or other service agencies—especially individual and contextual characteristics at the time when children enter out-of-home child welfare custody. Our data included publicly available census information, children's demographics, previous involvement with the child welfare system, past use of Medicaid services, and (for Florida) prior use of mental health and substance abuse services.

We examined the extent to which we could predict superutilization and identify predictive variables that may be important for agencies to monitor. To that end, a key challenge in developing a predictive model involves maximizing the ability to accurately predict children who truly experience superutilization and non-superutilization (i.e., true positives and true negatives, respectively) while minimizing the number of incorrect predictions (i.e., false positives and false negatives). Ultimately, how well the predictive model performs in achieving this goal is measured by overall classification accuracy, which we use as a key metric in choosing the final model. We discuss this and the various tradeoffs involved in greater detail below.

It is important to note that the predictive model we developed for this task is not a causal model. In discussing the results of the model in this chapter, we do not make any claims of causality. Moreover, we are limited in our ability to examine different mechanisms through which predictive variables may affect service utilization outcomes, which also restricts our ability to understand why some children who are predicted to experience superutilization do not.

Definitively answering questions related to why some children do not experience superutilization despite a high likelihood of doing so would require a causal research design, which is beyond the scope of this effort. However, the analysis conducted to answer the research question can provide useful insights with implications for practice. Accordingly, we discuss how the predictive findings could inform these types of questions.

This chapter begins with a discussion of the dependent variable for the predictive analysis. This variable is a specific indicator of superutilization—placement instability—that is of most interest to the study partners in Tennessee and Florida. Specifically, we aim to predict placement instability measured as a high number of out-of-home placement moves, which meets the threshold for superutilization as defined in Chapter V. The next section describes the data structure and measures used for the predictive analysis, which differs from what was presented in previous chapters for the descriptive and latent class analysis. We then summarize our analytic approach to predictive modeling, including examining specific components of model performance (e.g., the ability to predict true positives and true negatives) and interpreting key variables. We also briefly examine questions regarding those children who did not experience superutilization despite a high predictive likelihood (i.e., false positives), and then conclude with a discussion of the implications of our findings.

B. What outcome measure should we use?

One important finding highlighted in Chapter V was the high dimensionality and limited overlap between most measures of superutilization that we examined for the descriptive and latent class analyses. While we examined 10 measures for Tennessee and 11 measures for Florida that covered different domains of superutilization, most of these measures did not overlap with each other (as evidenced by relatively low correlations). The result is that children identified as experiencing superutilization on one measure (that is, by being at or above the 90th percentile for a given measure) are generally not the same children identified as experiencing superutilization on another measure. Given this observation, we determined, in consultation with our site partners, that predicting superutilization *in general* would not be as useful as predicting a *specific* measure of superutilization. If we predicted a specific measure, stakeholders in child welfare could better tailor their policies and practices to serve those children.

The project team engaged study partners in Tennessee and Florida to identify the most policy and practice relevant superutilization measure for predictive purposes in their local context. Based on these discussions, we focused on superutilization defined as the number of placement moves during an out-of-home custody episode, where a high number of placement moves indicates placement instability. Besides our partners' interest in this measure and its importance to child welfare service agencies more broadly, the number of placement moves within an out-of-home custody episode was also identified as a distinct cluster in the latent class analysis for both sites; the measure also had a high predicted probability in a second class (complex child welfare and Medicaid service use) in Florida.

Furthermore, focusing our predictive analysis on understanding placement moves would build on existing research. Multiple studies have focused on how many placements youth in foster care are experiencing (James 2004; Pecora et al. 2009). The results show a high variability in the number of placement changes; nationally, an average of 64.8 percent of children who were in foster care for 12 to 24 months have had a placement change more than once (ACYF 2016). As to why these changes occur, a study in Illinois (Zinn et al. 2006) uncovered the following reasons:

- The need to place a child with a sibling or other relative (38.7 percent of cases)
- One or more incidental events in a foster home (for example, a change in employment or family composition, an illness or death, and cessation of fostering in general) (30 percent of cases)

- Parents' inability to tolerate children's behavioral or emotional problems (27.6 percent of cases)

Although some reasons for placement change may be positive, such as to reunite a child with siblings or relatives or a step down in restrictiveness of the placement setting, these moves can negatively impact children's well-being and likelihood of achieving permanency. Placement stability is also preferable because it makes a child more likely to establish a stronger network of social support and enduring relationships with caring adults. Although more research is needed about the causes of and preventative mechanisms for placement changes, there is growing evidence that we should minimize these changes for at least five reasons (Figure VIII.1).

Figure VIII.I. Why does placement stability matter?

Physical and behavioral health:

- Children perceive placement changes as unsettling and confusing.[a]
- A child's satisfaction with the foster care system is inversely correlated with the number of placements he or she has had.[b]
- Placement changes can increase the risk of adolescent deviance (delinquency, drug use, alcohol use, school dropout, and status offenses).[c]
- Twenty-three percent of males in placement have a delinquency petition, compared with 11 percent who remain in the family home, further indicating correlation between placement instability and delinquency.[d]
- Over one-third (38 percent) of youth with two or more placements had visits to a hospital emergency department in the following year.[e]

Child attachment and emotional and behavioral disorders:

- Each change in placement reduces the opportunities for a child to attach to an adult and increases the chance that a child will develop emotional and behavioral disorders.[f]
- Children who have low to medium rates of placement change are 1.7 and 1.4 times more likely to have had no major mental health symptoms in the past 12 months compared with youth who have a high rate of placement changes.[g]
- Beyond an eight-month period in foster care, placement disruptions are associated with psychological deterioration.[h]

School mobility and academic achievement:

- One study indicated that students who have changed schools more than four times lose about one year of educational growth by their sixth school year.[i]
- High school students who change schools at least once are less than half as likely to graduate as their peers who do not change schools.[j]
- Children who change schools score 16 to 20 percent lower on standardized tests than children who do not change schools.[k]

Continuity of services, foster parents' stress, and program costs:

- Placement changes disrupt service provision, stress foster parents (thereby lowering retention rates), take up precious caseworker time, and create administrative-related disruptions.[l,m]
- Children moved to placements without siblings are at higher risk of experiencing placement disruption if they have a history of joint sibling placements.[n]

Potential for child to establish a relationship with caring adult:

- The more stability a child has, the more likely it is that he or she will be able to develop enduring positive relationships with adults who care about him or her.[o]

Sources: Pecora, P.J., and S.C. Boling. *Improving placement stability in the foster care system*. Seattle, WA: Research Services, Casey Family Programs, 2017; Pecora, P.J., and D. Huston. "Why Should Child Welfare and Schools Focus on Minimizing Placement Change as Part of Permanency Planning for Children?" *Social Work Now*, 2008, pp. 19–27.

[a]Festinger, T. *No One Ever Asked Us*. A Postscript to Foster Care. New York: Columbia University Press, 1983.

[b]Pecora, P.J., and D. Huston. "Why Should Child Welfare and Schools Focus on Minimizing Placement Change as Part of Permanency Planning for Children?" *Social Work Now*, 2008, pp. 19–27.

[c]Herrenkohl, E., R. Herrenkohl, and B. Egolf. "The Psychosocial Consequences of Living Environment Instability on Maltreated Children." *American Journal of Orthopsychiatry*, vol. 73, no. 4, 2003, pp. 367–380.

[d]Ryan, J., and M. Testa. "Child Maltreatment and Juvenile Delinquency: Investigating the Role of Placement and Placement Instability." Champaign-Urbana, IL: University of Illinois at Urbana-Champaign School of Social Work, Children and Family Research Center, 2004.

[e]Rubin, D.M., E.A. Alessandrini, C. Feudtner, A.R. Localio, and T. Hadley. "Placement Changes and Emergency Department Visits in the First Year of Foster Care." *Pediatrics*, vol. 114, no. 3, 2004, pp. 354–360.

[f]Pecora, P.J., and D. Huston. "Why Should Child Welfare and Schools Focus on Minimizing Placement Change as Part of Permanency Planning for Children?" *Social Work Now*, 2008, pp. 19–27.

[g]O'Brien, K., R.C. Kessler, E. Hiripi, P.J. Pecora, C.R. White, and J. Williams. "Working Paper No. 7: Effects of Foster Care Experiences on Alumni Outcomes: A Multivariate Analysis." Seattle, WA: Casey Family Programs, 2008.

[h]Barber, J., and P. Delfabbro. *Children in Foster Care*. New York: Routledge, 2004.

[i]Kerbow, D. "Patterns of Urban Student Mobility and Local School Reform." *Journal of Education for Students Placed at Risk,* vol. 1, no. 2, 1996, pp. 147−169.

[j]Rumberger, R., and K.A. Larson. "Student Mobility and the Increased Risk of High School Dropout." *American Journal of Education*, vol. 107, 1998, pp. 1−35.

[k]Calvin, E.M. *Make a Difference in a Child's Life: A Manual for Helping Children and Youth Get What They Need in School: Advocating for Children and Youth Who Are Out of Home or in Foster Care*. Seattle: TeamChild and Casey Family Programs, 2000.

[l]Flower, C., J. McDonald, and M. Sumski. "Review of Turnover in Milwaukee County Private Agency Child Welfare Ongoing Case Management Staff." Milwaukee, WI: Milwaukee County Department of Social Services, 2005.

[m]James, S. "Why Do Foster Care Placements Disrupt? An Investigation of Reasons for Placement Change in Foster Care." *The Social Service Review*, 2004, pp. 601−627.

[n]Leathers, S.J. "Separation from Siblings: Associations with Placement Adaptation and Outcomes Among Adolescents in Long-Term Foster Care." *Children and Youth Services Review*, vol. 27, 2005, pp. 793–819.

[o]Pecora, P.J., and D. Huston. "Why Should Child Welfare and Schools Focus on Minimizing Placement Change as Part of Permanency Planning for Children?" *Social Work Now*, 2008, pp. 19–27.

In summary, placement moves are an important dynamic to monitor closely because placement stability maximizes continuity in services, decreases stress among foster parents, lowers program costs, and can improve child well-being, which depends and stability and security. A high number of placement moves, on the other hand, can interrupt service provision, place pressure on foster parents (possibly causing them to stop fostering), take up caseworkers' time, and disrupt administrative processes. But because we know so little about what predicts these moves, the field is less able to prevent them.

Below, we describe our approach to developing a model to predict superutilization defined as the number of placement moves.

C. Data structure and measures for predictive modeling

Unlike the sample time frame that we used for the descriptive and latent class analyses, the predictive analysis required an alternative restriction and structuring of the data, creating a different study sample. In general, predictive modeling often requires that the data be structured in a way that separates the prediction period from the lookback period. The *prediction period* is the interval during which the outcome of interest (that is, superutilization based on placement moves) is measured and the actual prediction of the outcome is estimated. The *lookback period* is the interval before the prediction period that provides variables used for prediction. Typically, the prediction and lookback periods are of equal length so that the analysis and interpretation is balanced and consistent. Below, we discuss how the data were structured for the predictive analysis in Tennessee and Florida.

1. Defining the prediction and lookback periods

For both Tennessee and Florida, we used a 12-month prediction period and a 12-month lookback period, which are anchored by the custody episode start date. This translates into a one-year period from time of entry into custody during which predictions of superutilization can be made and a one-year lookback period, prior to entering custody, during which information used to predict superutilization could also be measured. The 12-month periods were selected in consultation with the study team and site partners to ensure that the intervals produced informative and relevant data. Prediction intervals that exceed 12 months may result in less accurate predictions and can be more challenging for administrators in terms of planning.

Despite the 12-month limit for the lookback period, three child welfare variables are based on the full history of a child, which may extend beyond 12 months (such as prior child welfare investigations, prior custody episodes, and total length of stay in prior custody episodes). These measures are potentially important because they may capture a longer history of past child welfare involvement, which could be useful for prediction. However, most of our measures were only available for a year, so we use the term, 12-month lookback period, as shorthand to cover all predictor variables.

To create the prediction and lookback periods, we needed to select samples for each site with a time interval that would allow for both a 12-month lookback and prediction period without being censored by the study window. For Tennessee, the study data covered July 1, 2011, to December 31, 2015. To create a balanced data set with 12 months on either side of the time period for the predictive analysis sample, we calculated the applicable time period for the predictive analysis sample as spanning from July 1, 2012, to December 31, 2014. In practice, a sample member's 12 month lookback and prediction periods will vary according to their specific episode start date, making them unique to each child.

The Florida data for most site partners covered January 2011 to December 2015. As noted previously, because Eckerd provided CBC-purchased services data for a shorter time period than this, the sample for the descriptive and latent class analysis was limited to September 1, 2013, to December 31, 2015. But for predictive modeling, this restriction limited our ability to use 12-month lookback and prediction periods. In consultation with our Florida site partners, we agreed to use the full five-year study window to structure the data for the predictive analysis and to exclude the CBC-purchased services data, which were available for a very small portion of the sample for a short period. Therefore, we used the full time frames for which child welfare, Medicaid, and SAMH data were available—January 1, 2011, to December 31, 2015. To include 12-month lookback and prediction periods, we calculated a qualifying time interval for the predictive analysis sample of January 1, 2012, to December 31, 2014.

2. Measuring superutilization defined as the number of placement moves

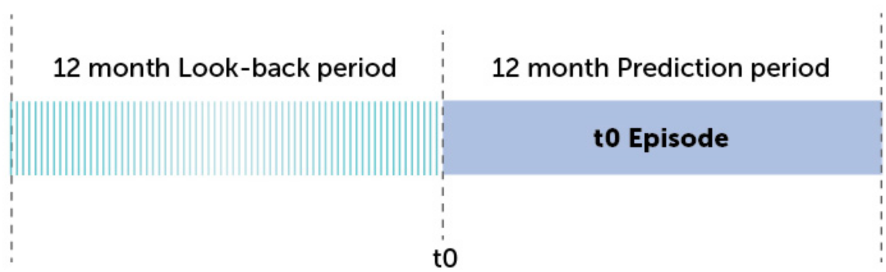
After revising the time periods for the predictive analysis for Tennessee and Florida, we further refined the data to measure the key outcome of interest—superutilization defined as the number of placement moves during the prediction period. To structure the data for the analysis, we performed additional data management, as described below.

a. First out-of-home custody episode in the prediction period

We identified the first out-of-home custody episode as the starting point for the 12-month prediction period. This first episode (also referred to as the t0 episode) is the episode during which we measured all placement moves for the purpose of defining superutilization. For Tennessee, the first out-of-home custody episode is defined as the first custodial episode that started between July 1, 2012, and January 1, 2014. For Florida, the first out-of-home custody episode is defined as the first child welfare out-of-home placement during episodes that started between January 1, 2012, and January 1, 2014. (We also refer to this as the first custody episode because, when children had more than one episode during the prediction period, we only selected the first one.)

This first out-of-home custody episode is also the unit to which our predictions of superutilization apply. The duration of the first episode can span up to the full 12-month prediction period, but it can also be shorter. For measurement purposes, if the t0 episode went beyond the 12-month prediction period, we censored the measurement at 12 months. Alternatively, if the t0 episode was less than 12 months, we used the actual end date to mark the end of the measurement period. Figure VIII.2 depicts the general structure of the data for the 12-month lookback and prediction periods in relation to the out-of-home custody (t0) episode. It should be noted that while the figure shows the t0 episode spanning the entire 12 month period, this does not have to be the case. In practice, the t0 episode can be less than, equal to, or more than 12 months in duration (though we truncate the actual duration at 12 months, as discussed below).

Figure VIII.2. Prediction and lookback periods in relation to the t0 episode



There are several reasons why we defined the measurement interval this way. First, as a practical consideration, prediction is more easily conceptualized and measured within a single custody episode that has a clearly defined beginning and end date. By restricting measurement of superutilization to the first out-of-home custody episode in the study window, the model is clearly and consistently defined for all children in the sample and is easier to interpret. Second, a custody episode is a meaningful level of analysis for child welfare policy and practice. Third, we believe a focus on episodes helps to minimize the effects of censoring the data. Although right-censoring is still a potential concern (due to censoring the measurement in the out-of-home custody episode if it exceeds 12 months), the effects will be minimized if we define a consistent time window for all episodes. By contrast, if we measured superutilization at the child level without structuring the data by episode, it would be difficult to account for censoring because children can enter the system at any time, and the period covered by the data would essentially be arbitrary. (Please note, however, that our measurement largely equates the episode level to the child level because we only use the first out-of-home custody episode for each child, given no subsequent episodes are included in the predictive analysis.)

We also chose to focus on a single episode rather than several during the prediction period because it's more analytically useful; the predictors in the lookback period may not be as useful for predicting multiple moves within sequential episodes. Moreover, if we used several episodes in the prediction window to measure superutilization, intervening factors may occur between episodes, and it would be difficult to tell which of these factors may have affected later episodes.

After restricting the measurement to the first out-of-home custody episode in the prediction period, we examined the total sample sizes for both study sites. In Tennessee, 12,056 children had t0 episodes, whereas 8,290 children had t0 episodes in Florida. As expected—due to the requirements for the predictive modeling time frame—Tennessee's sample size was smaller in this analysis than it was in the descriptive analysis. In contrast, Florida's sample size was larger due to the exclusion of the Eckerd service data that limited the timeframe for the descriptive and latent class modeling.

As we discuss below, the sample sizes for both sites were sufficient for a robust approach to modeling and validation. Before describing the modeling approach, we first discuss the measurement of superutilization based on placement moves and the characteristics of the predictive samples for each site.

b. Defining superutilization thresholds for the number of placement moves

Having both structured the data for predictive modeling and ensured adequate sample size, the next step was to formally measure placement instability defined as the threshold for superutilization for the number of placement moves. Consistent with the approach discussed in Chapter V, we defined superutilizers as youth who equaled or exceeded the 90th percentile value on the distribution of the total number of placement moves within the first out-of-home custody episode during the prediction period.[12] The 90th percentile threshold for Tennessee was four moves in the 12-month period, and for Florida, the threshold was five moves.

Once we calculated these values, we created a binary variable to indicate whether the number of placement moves during the episode equaled or exceeded the superutilization threshold. Twenty percent of the Tennessee sample and 14 percent of the Florida sample were flagged as superutilizers based on this criterion.[13] This binary measure of superutilization served as our dependent variable, where we sought to predict whether a sample member did or did not

[12] Unlike in the latent class analysis, the placement moves measure was not age-adjusted in the predictive analysis. Instead, we accounted for age by including it as part of our prediction model, which takes into account potential confounding in the relationship between age and superutilization status by other predictors.

[13] The proportion of the sample flagged as experiencing superutilization exceeds 10 percent of the sample. This is a function of both the skewed distribution of the values on the placement moves variable and a large number of similar values clustered close to the 90th percentile (e.g., the same value at the 89th percentile as at the 90th percentile). As such, the top decile of the distribution of values for placement moves translates to a higher proportion of children flagged as experiencing superutilization in the sample.

experience superutilization on this measure. VIII.1 summarizes the key descriptive statistics for the dependent variable for Tennessee and Florida.

VIII.1. Placement Instability outcome: Number of placement moves in 12-month prediction period

	Distribution				
	Mean	Standard deviation	Minimum	Maximum	P90 threshold
Tennessee	2.6	1.7	0	25	4
Florida	3.3	4.3	1	84	5

Source: Tennessee DCS; Florida OCW.

3. Sample characteristics

As discussed above, preparing the data for predictive modeling required using a subset of the full data for each site. Once we applied the time restrictions for the prediction and lookback periods, the final sample for Tennessee was smaller than the one used for the descriptive and latent class analysis. Conversely, the Florida sample was larger than the one used for the descriptive and latent class work due to the exclusion of Eckerd services data.

Although we assumed that the composition of children entering the child welfare system was essentially random over time, the characteristics of the sample used in the predictive model may differ from those of the full sample. Below, we provide summary statistics for the Tennessee and Florida predictive samples.

a. Tennessee

In general, the Tennessee sample had a relatively balanced distribution of children across age categories at the first out-of-home custody episode (VIII.2). The proportions across the age categories were nearly identical to those reported for the full latent class modeling sample in Chapter III. The same was true of the distribution by gender and the proportion of children whose race was reported as white or black. The regional distribution of the sample as shown in VIII.3 was also very similar to the distribution for the full sample discussed in Chapter III with the exception of the proportion of the sample from the SIU which is notably lower than the full sample.

VIII.2. Demographics of the Predictive Sample for Tennessee

	Tennessee		Florida	
	Number of children	Percentage of children	Number of children	Percentage of children
Age at T_0				
Less than 1 year old	1,948	16.2	1,729	20.9
1 to less than 6 years old	3,340	27.7	3,002	36.2
6 to less than 13 years old	3,376	28.0	2,343	28.3
13 to less than 18 years old	3,384	28.1	1,213	14.6
18 to less than 24 years old[a]	3	0.0	0	0.0
Missing	5	0.0	3	0.0
Gender				
Male	6,144	51.0	4,180	50.4
Female	5,905	49.0	4,110	49.6
Unknown	7	0.1	0	0.0
Race/ethnicity				
White	9,361	77.6	5,898	71.1
Black	3,000	24.9	2,876	34.7
Hispanic/Latino	629	5.2	1,172	14.1
Asian	29	0.2	43	0.5
American Indian/Alaska Native	47	0.4	20	0.2
Native Hawaiian/Pacific Islander	23	0.2	19	0.2
Multiracial when one race is unknown[b]	29	0.2	–	–
Missing	208	1.7	54	0.7
Number of children	**12,056**		**8,290**	

Source: Tennessee DCS; TennCare; Florida OCW; Florida AHCA data; Florida SAMH.

Note: Race and ethnicity values are not mutually exclusive.

[a]In Florida, age information was set to “missing” for all children with reported ages of 23 and older. In Tennessee, age information was set to “missing” for all children with reported ages of 24 and older. These cutoffs are consistent with the age restrictions for extended foster care in each state.

[b]“Multiracial when one race is unknown” is a SACWIS race value selected for people who are suspected or known to be more than one race but for whom only one race has been identified. This category is reported by Tennessee only.

VIII.3. Tennessee's predictive sample by DCS region

	Number of children	Percentage of children
DCS regions		
Davidson	614	5.1
East Tennessee	879	7.3
Knox	986	8.2
Mid-Cumberland	1,230	10.2
Northeast	917	7.6
Northwest	437	3.6
Shelby	1,074	8.9
Smoky Mountain	1,082	9.0
South Central	546	4.5
Southwest	516	4.3
Tennessee Valley	979	8.1
Upper Cumberland	1,144	9.5
Child abuse hotline	3	0.0
DCS central office	2	0.0
SIU	64	0.5
Missing	1,583	13.1
Number of children	**12,056**	

Source: Tennessee DCS; TennCare.

Note: Children were allocated to the region associated with their T0 episode. A map of Tennessee DCS regions can be found via the following link: https://www.tn.gov/assets/entities/dcs/attachments/DCS_Regional_Map_June_2016.pdf.

b. Florida

As discussed previously, the Florida sample used for the predictive modeling was larger than the sample examined in the descriptive and latent class work because we were not restricted by the smaller study window for Eckerd services data. Despite this difference, the characteristics of the predictive sample for Florida, as shown below in Tables VIII.4 and VIII.5, were very similar to those summarized in for the sample described in Chapter III. The distribution of children by county was also similar, with the minor exception of a slightly smaller proportion in Hillsborough County (44 percent for the predictive sample versus 51 percent for the descriptive sample described in Chapter III).

VIII.4. Florida's predictive sample by county

County	Number of children	Percentage of children
Hillsborough	3,657	44.1
Pasco	1,631	19.7
Pinellas	2,312	27.9
Other	690	8.3
Number of children	**8,290**	

Source: Florida OCW; Florida AHCA data; Florida SAMH.

Note: Children were allocated to the county associated with their T0 episode, which may be a county other than Hillsborough, Pasco, or Pinellas if the child had more than one episode during the study window.

D. Approach to predictive modeling

This section describes our approach to predicting superutilization. To streamline the discussion, we first summarize the variables used for prediction in Tennessee and Florida. Next, we elaborate on our approach to estimating and validating the models we examined. We also discuss the three types of predictive models we compared before selecting the final model based on prespecified performance criteria. The results presented in the remainder of the chapter are based on the final model. Below, we provide an overview of the predictors used in the analysis for Tennessee and Florida. We then discuss our general approach to model selection and the definitions of key metrics that are useful for interpretation.

1. Predictors and missing values

To examine how well we can predict superutilization defined as the number of placement moves, we modeled the probability of superutilization as a function of several predictor variables from the lookback period (12 months before the episode) or from the full history of the child (that is, child welfare variables collected earlier than the lookback period and measured up to the first out-of-home placement episode). In specifying these variables, we relied on the expertise of the project team and site partners and on insights gained from reviewing other predictive models in child welfare (for example, Vaithianathan et al. 2017).

In addition to theoretical relevance, another key consideration in the model specifications was that the variables be generally available to child welfare agencies and that the methods be entirely replicable. To that end, our predictors included lagged values of most of the child welfare and Medicaid measures that we examined in the descriptive and latent class analyses. As noted above, we also included three variables that were measured based on the child's history before the t0 episode—the number of prior child welfare investigations, the number of prior custody episodes, and the total length of stay in days in prior episodes. Full-history information on these measures would be available to child welfare agencies when they review a case upon entry into out-of-home custody; therefore, we considered this information potentially useful for predictive purposes. In addition, we included child demographic data and regional demographic variables that are publicly available from the American Community Survey and U.S. Census. We included regional variables based on feedback from the sites and because contextual variation across regions might add information useful for prediction.

Although we attempted to keep the models as consistent as possible by using the same types of predictors for both Tennessee and Florida, not all variables were available for both states. In Tennessee, for example, we were able to use data on the number of prior child welfare investigations, reasons for removal associated with the t0 custody episode, and the number of custodial and noncustodial child welfare services received during the lookback period. These variables were not available for Florida. However, the Florida model specification included measures for SAMH mental health and substance abuse services received during the lookback period, which was unique to the Florida sample. In addition, Tennessee and Florida use different child assessments, which we included in the models.

A common issue with any data analysis is the presence of missing values on key variables of interest. Many of the variables we examined had a high incidence of missingness. In some cases, missing values were expected because the measure in question only applied to certain children for reasons that were clearly understood and documented. In other cases, values were missing for unknown reasons. In line with more common practices in the statistical literature, we considered missing values to be potentially informative for predictive purposes (Little and Rubin 2002). Accordingly, we created indicators for missing values based on the method developed by Twala et al. (2008), known as the missingness in attributes (MIA) approach. This enabled us to incorporate information on the patterns of missing values into the predictive model without dropping variables—a potential source of bias (Little and Rubin 2002). We provide details on the MIA approach in Appendix E.

a. Tennessee

We used a total of 65 predictor variables in the final model, including variables in domains shown in VIII.5 (a discussion of the process used to select the final model is provided in Appendix E; a full list of variables are provided in Appendix E Tables E.1 and E.2). Each domain included one or more variables that would be available to child welfare agencies.

VIII.5. Variable domains for Tennessee predictive model

Variable domain	Description
Child demographic characteristics	Age, race, and gender
Prior investigations	Number of prior child welfare investigations
Reason for removal	Reason for removal
Foster care placements	Number of placement moves and average percentage of time in group/congregate care
Child welfare custodial episodes	Number of prior child welfare custodial episodes and total length of stay (in days) in prior custodial episodes
Child welfare services	Number of custodial and noncustodial child welfare services
Child welfare assessments	Average results from CANS, FAST, YLS, and Ansell-Casey Life Skills assessments
Average recommended service level across prior investigations	Average recommended service level (no services needed, services recommended, services required) across prior investigations
Medicaid services	Number of inpatient, outpatient, and emergency behavioral and physical health services
DCS region composition	DCS region-level demographic information, including regional racial composition, percentage of married households, percent foreign born, percentage with a high school diploma or equivalent, percent unemployed, poverty status, and urbanicity

b. Florida

We used a total of 53 variables, including variables listed in the domains shown in VIII.6 (a full list of variables is provided in Appendix E, Tables E.3 and E.4).

VIII.6. Variable domains for Florida predictive model

Variable domain	Description
Child demographic characteristics	Age, race, and gender
Prior investigations	Number of prior child welfare investigations
Foster care placements	Number of placement moves and average percentage of time in group/residential care
Child welfare custodial episodes	Number of prior child welfare episodes and total length of stay (in days) in prior out-of-home foster care placements
SAMH	Number of substance abuse and mental health services
SAMH assessments	Average results of CFARS and ASAM assessments
Average child welfare investigation risk level associated with the episode	Average recommended service level (no services needed, services recommended, services required) across prior investigations
Medicaid services	Number of inpatient, outpatient, and emergency behavioral and physical health services
OCW region composition	OCW region-level demographic information, including regional racial composition, percent foreign born, percentage with a high school diploma or equivalent, percent unemployed, poverty status, and urbanicity

2. Approach to model development and selection

A critical component of predictive modeling is the need to balance the overall fit of the statistical model with the ability to make accurate predictions about children who were not included in fitting the model (that is, out-of-sample predictions). In fact, these two desirable features of a predictive model can work in opposition to each other, as overfitting a model can lead to poor predictions about children who were not part of the model.

Given the goal of predicting superutilization based on placement moves, achieving strong out-of-sample performance is critical. We therefore created a "training" and "test" data set (also referred to as a hold-out sample) for both Tennessee and Florida using the predictive analysis sample described earlier in this chapter. This was done by randomly splitting the sample into training and test data sets to be used for model development and model validation, respectively (James et al. 2013). As part of this process, we needed to determine what proportion of the total sample should be split into training and test sets. Based on several considerations, including the total sample sizes and number of covariates, we used a 70/30 split for Tennessee and Florida (Hastie et al. 2009). In other words, 70 percent of the sample for both Tennessee and Florida was used to develop (or train) the models, whereas the remaining 30 percent was used to validate model results. Although these splits were random, we added a stratification constraint to ensure that the proportion of superutilizers present in both samples was the same. Specifically, we split the Tennessee data to ensure that children who experienced placement instability accounted for 20 percent of the training and test data sets; similarly, for Florida, we ensured that 14 percent of both samples were consisted of children who experienced placement instability.

Note that all comparisons of model performance in terms of different variable specifications and types of models (discussed below) were based only on the training data. At no point in the modeling process was the test sample allowed to influence the model specification. Ultimately, how well the model performs on the test data set is of key interest; however, applying the selected model to the test data is the final step.

Using the training data, we examined the performance of three general approaches to predictive modeling that vary in terms of their flexibility to predict binary outcomes, such as our outcome variable of superutilization defined as the number of placement moves. The three models we considered were (1) logistic regression with elastic net regularization (EN), (2) K-nearest neighbors (KNN), and (3) random forests (RF). We provide further technical details about these models, their pros and cons, and their comparative predictive performance in Appendix E.

As noted above, the general goal of predictive modeling is to achieve a high level of overall classification accuracy. This means that we are looking for a model that can correctly identify children who experience superutilization and distinguish them from those who do not with a high degree of accuracy, given the information in the model. In addition, the predictive model should minimize the proportion of incorrect classifications (i.e., minimize the number of false positives and false negatives). How well our model achieves the goal of overall classification accuracy is the main criterion by which we assessed and selected our final statistical model. For purposes of final model selection, the statistical measure that best captures overall model classification accuracy is the Area Under the Receiver Operator Characteristic Curve (AUC), which we introduce briefly below. In short, we selected the final prediction model based on the highest value of the AUC.

- **Area Under the Receiver Operator Characteristic Curve (AUC).** The AUC is a summary measure of overall model predictive performance, which in this case refers to how well the model correctly classifies children who experience superutilization compared to children who do not. More formally, the AUC measures the area under the Receiver Operator Characteristic Curve (ROC), which summarizes the model's ability to correctly identify children who experience superutilization (i.e., true positives) while minimizing the number of children who are incorrectly classified as experiencing superutilization when they do not (i.e., minimizing the rate of false positives). The AUC ranges from 0 to 1, with higher values indicating better prediction. The AUC can be interpreted as the probability that a randomly selected child experiencing superutilization will have a higher predicted probability of being identified as experiencing superutilization, conditional on the model, than a randomly selected child who does not experience superutilization. Higher AUC values indicate that this probability is greater for a randomly selected child who experienced superutilization versus non-superutilization. Typically, AUC values greater than 0.70 are considered indicative of good predictive performance in most social science settings (Rice and Harris 2005).

We used the AUC as our measure of overall model performance. However, we also examined several other measures when evaluating model performance. These measures are defined briefly below and are discussed further in the findings section. While these measures are useful for interpretation purposes, they did not inform our final model selection process because, unlike the AUC itself, these measures can be manipulated after model estimation by setting different threshold values for the predicted probabilities used to classify children as likely to experience superutilization or not. Therefore, while these measures—particularly, sensitivity and specificity—are important when discussing policy implications, they did not inform final model selection.

- **Sensitivity.** This is the true positive rate of superutilization. Specifically, sensitivity measures the ability of the model to correctly identify children who experience superutilization defined as the number of placement moves.
- **Specificity.** This is the true negative rate of superutilization. Specificity measures the ability of the model to correctly identify children who do not experience superutilization.
- **Accuracy.** This is a measure of agreement between children's superutilization classification, as predicted by the model, compared to their actual classification. Accuracy is a weighted function of sensitivity and specificity. The weight in this case is the prevalence of superutilization in the sample. Formally, accuracy equals sensitivity multiplied by prevalence plus specificity multiplied by one minus prevalence.
- **Positive Predictive Value (PPV).** The PPV measures the probability that a child classified as experiencing superutilization actually does experience superutilization (i.e., is a true positive when identified as experienced superutilization).

- **Negative Predictive Value (NPV).** The NPV measures the probability that a child classified as not experiencing superutilization actually does not experience superutilization (i.e., is a true negative when identified as not experiencing superutilization).

E. Findings from the predictive analysis

In this section, we answer the key research question regarding what characteristics at the time of entry into an out-of-home placement predict the superutilization measure of high placement instability. In reporting the results for each state, we first discuss the overall performance of the RF models based on the test data. In comparing the predictive performance of the RF relative to the EN and KNN models, the RF consistently achieved the highest AUC and was therefore deemed superior (we provide comparative performance statistics in Appendix E). Therefore, all results discussed below are based solely on the predictions applied to the test data from the RF models. After discussing overall performance, we examine which variables emerged as the most important predictors for both states.

1. Tennessee

a. Overall model performance

VIII.7 shows the overall predictive performance of the RF model for Tennessee. The lists the summary statistical measures that were defined above which assess different aspects of model performance. In general, the findings show that it is possible to predict high placement instability with a reasonable degree of accuracy. As noted earlier, a primary measure of predictive performance is the AUC. For Tennessee, the AUC on the test sample was 0.727. The AUC of 0.727 suggests that the model performs well when distinguishing a child who experienced superutilization from a child who did not.

VIII.7 also shows several other summary performance statistics. But keep in mind that these measures are ultimately a function of the AUC and the prevalence of children experiencing superutilization in the sample. As such, the measures provide additional ways to interpret different aspects of predictive performance, but they do not provide an overall assessment of predictive performance. As such, although many of these measures may be of interest to researchers or practitioners, they should be interpreted with certain caveats in mind, as discussed below.

The third and fourth columns of VIII.7 show the sensitivity and specificity of the model. As defined above, sensitivity is the true positive rate (the ability of the model to correctly identify children who experience superutilization). Specificity is the true negative rate (the ability of the model to correctly identify children who do not experience superutilization). One policy-relevant consideration we made when tuning the model was that it was more important to identify true positives than it was to identify true negatives. That is, we decided that increasing sensitivity at the expense of lowering specificity was key. Tuning the model this way is based on our ability to choose different thresholds (cut points) based on the predicted probabilities of experiencing high placement instability. Based on the model, we can choose different cut points for determining which children are predicted to experience high placement instability. Choosing a lower cut point results in predicting that more children will experience placement instability. Conversely, choosing a higher cut point will result in predicting that fewer children will experience placement instability. In many cases, a predicted probability of 0.5 would serve as a default cut point for predictive purposes. However, because placement instability is relatively rare (applying to only 20 percent of the Tennessee sample), using this default probability would result in identifying very few children as experiencing placement instability (well below the true 20 percent rate). Instead, in order to increase sensitivity, we used a cut point of 0.16, which was based on the point closest to upper left-hand corner of the ROC Curve. We provide more technical details about this process in Appendix E. However, the key point to note here is that selecting a higher or lower cut point results in a tradeoff between sensitivity and specificity. It is important to emphasize here that the choice of cut point is ultimately a policy, rather than a statistical, decision.

Another measure we report is accuracy, which is a weighted function of sensitivity and specificity. The weight in this case is the prevalence rate of true superutilization in the sample, which is 20 percent for Tennessee. Given this relatively low prevalence, the accuracy is largely driven by the ability to identify children who do not experience superutilization, which is the majority of the sample.

Finally, VIII.7 shows the model's positive predictive value (PPV) and negative predictive value (NPV). As defined above, the PPV reports the probability that children predicted by the model to experience placement instability actually do so. As the table below summarizes, the PPV was relatively low whereas the NPV (the probability that children predicted not to experience placement instability actually do not) was high. These results are not surprising given the fact that the prevalence of superutilization was only 20 percent, which means that most children identified as experiencing placement instability actually do not. As noted above in the context of sensitivity and specificity, these results reflect the decision to use lower cut points to define which children are predicted to experience placement instability. Overall, however, the model appears to distinguish children who will experience superutilization from those who will not with a reasonable degree of power.

VIII.7. Tennessee: RF model's predictive performance with the test sample

AUC	Accuracy	Sensitivity	Specificity	PPV	NPV
0.727	0.673	0.682	0.671	0.342	0.893

Source: Tennessee DCS; TennCare; American Community Survey 2015; Census 2010.

Note: N = 3,617. **AUC** = area under the ROC curve; **accuracy** = (prevalence)*sensitivity + (1-prevalence)*specificity; **sensitivity** = true positive rate of superutilization; **specificity** = true negative rate of nonsuperutilization; **PPV** = positive predictive value, or the probability that children classified as superutilizers truly are superutilizers; **NPV** = negative predictive value, or the probability that children classified as nonsuperutilizers are truly nonsuperutilizers.

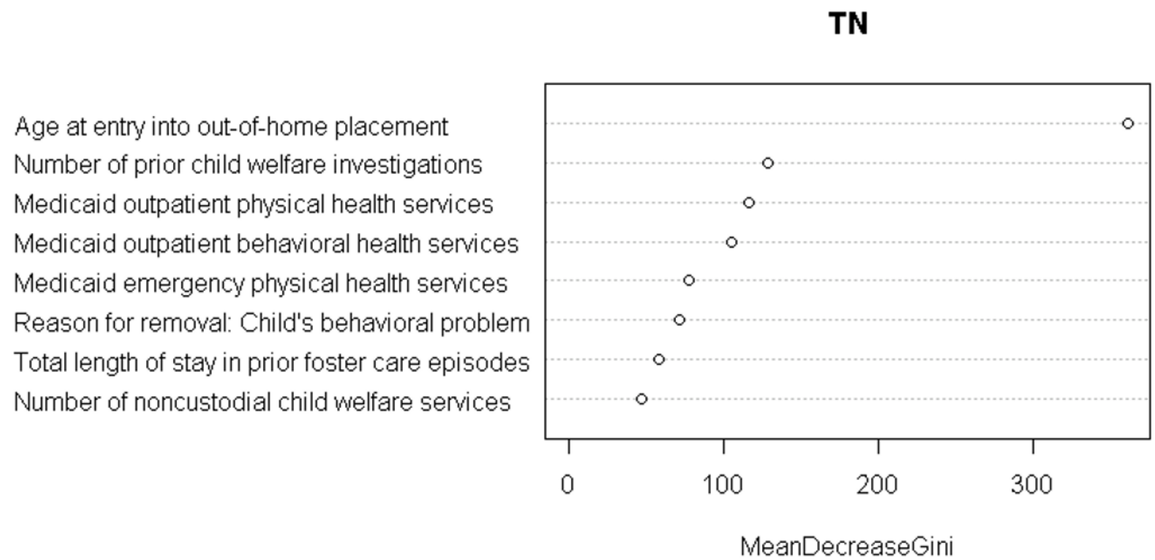
b. Interpreting variable importance

With a predictive model that performs well, we can answer the key research question about which characteristics predict superutilization, based on the number of placement moves. Although our focus up to now has been on overall predictive performance, it's perhaps even more relevant to child welfare agencies to know which variables may be important to monitor for assessing a child's risk of experiencing superutilization.

The results of the RF model indicate the relative importance of the variables by showing how each contributes to the overall model fit. For RF models, this can be determined by ranking individual predictors based on the mean percentage change in the Gini impurity index (James et al. 2013). This index measures the change in overall model fit that a given predictor contributes, with higher values indicating a greater contribution.

Figure VIII.3 lists the 8 most important predictors based on the mean change in the Gini index. Based on the rankings, a child's age at entry into the first out-of-home placement during the prediction period is the most important variable by a wide margin (the mean decrease in the Gini index is over 350), followed by the number of prior investigations. Note that the next eight variables all appear to cluster together in terms of the change in the mean Gini index.

Figure VIII.3. Eight most important predictors for placement instability superutilization in Tennessee



Source: Tennessee DCS; TennCare; American Community Survey 2015; Census 2010.

To streamline the discussion, we provide the marginal predicted probabilities (partial density plots) of superutilization for the 8 most important predictors based on their relative rank according to the Gini index. Figure VIII.4 is a 5 x 2 matrix plot showing the change in the predicted probability of superutilization based on the different values of the 10 variables. The variables are listed in order of importance, from 1 to 10, based on their change in the Gini index. Thus, the upper-left portion of each cell in the figure provides the numerical ranking of importance for each variable.

As shown in the figure, the most important predictor is a child's age at entry into the first out-of-home placement in the prediction period. The first plot shows that the predicted probability of experiencing superutilization based on placement instability is relatively steady for children at younger ages before increasing notably between ages 11 and 12. Eleven-year-olds have a 0.15 predicted probability of experiencing superutilization, which increases to 0.20 at age

12 (a 33 percent increase). Children ages 15 and 16 have the highest probability of experiencing superutilization. This suggests that child welfare agencies may want to focus on certain age groups, specifically adolescents.

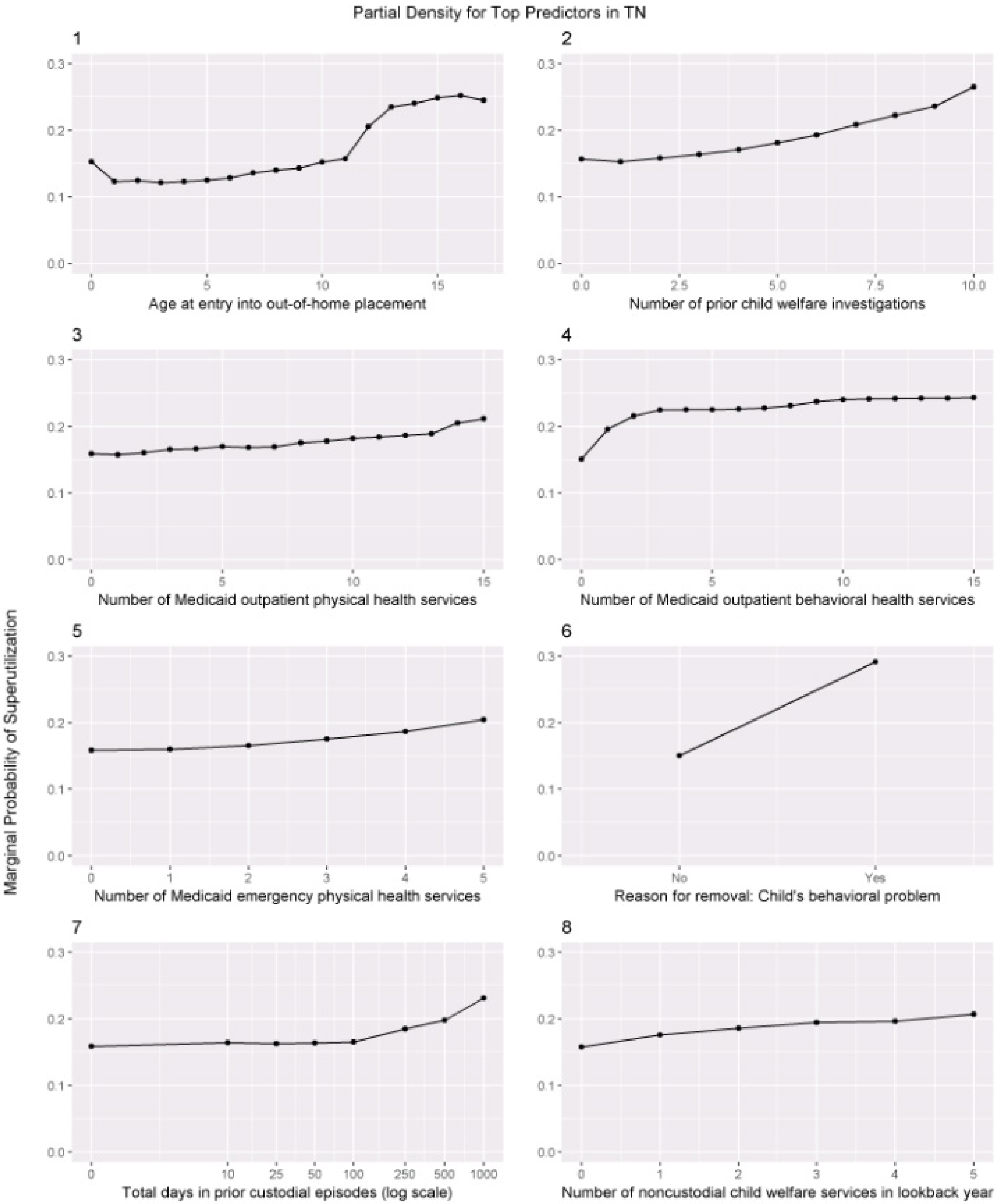
The second most important predictor for Tennessee is the number of prior child welfare investigations before the investigation associated with the t0 episode. The pattern suggests a somewhat linear increase in the probability of experiencing several placement moves as the number of prior investigations increase.

The third, fourth, and fifth most important predictors all relate to prior receipt of Medicaid services for outpatient physical and behavioral health and emergency physical health. Although the magnitude of change in the Medicaid measures is not particularly high, the fact that these variables seem to have predictive strength suggests that it may be useful for child welfare agencies to know about Medicaid service history at the time of entry into custody.

Another variable that may be useful to monitor is the reason for removal associated with the t0 episode when that reason is a child behavioral problem. A behavioral problem is not an allegation type and refers to situations in which the child enters custody through the court and has behavioral issues that the parents cannot resolve (such as aggression, chronic runaway behaviors, and oppositional defiance). Case managers can check multiple reasons for removal, so they may check this box in addition to the allegation that resulted in the child's removal if the child has major behavioral problems that the parents cannot address. Specifically, the predicted probability of experiencing placement instability increases from a baseline of 0.15 when behavioral problems are not indicated as a reason for removal (x axis = 0) to a probability of 0.30 when behavioral problems are identified (x axis = 1). This suggests that the relative risk of experiencing superutilization doubles when behavioral problems are a reason for removal in the t0 episode.

Another variable that may also be of interest is the number of noncustodial child welfare services. These are services provided to children while they remain at home with their parents. In low-risk situations, noncustodial services are often a useful way to provide support to families without having to remove the child. Although the slope of the marginal predicted probability is not steep, there is a no linear increase in the predicted probability as the number of noncustodial services received in the lookback period increases.

Figure VIII.4. Tennessee: Eight most important predictors of superutilization based on placement moves



Source: Tennessee DCS; TennCare; American Community Survey 2015; Census 2010.

2. Florida

a. Overall model performance

In general, despite a different model specification (see Tables E.1 and E.2), the overall predictive performance of the model for Florida was similar to that of Tennessee. As shown in VIII.8, the AUC for Florida was 0.722, which is very close to the AUC for Tennessee. Again, we interpret this to mean that it is possible to predict placement instability with a reasonable degree of confidence, conditional on having similar information in the model.

Regarding the other measures shown in VIII.8, the accuracy value for Florida is slightly higher than the same value for Tennessee. The main reason for this is related to the prevalence of superutilization in the Florida sample—14 percent overall—which is lower than the proportion in Tennessee (20 percent). The accuracy is higher in Florida because the model performs well in identifying children who do *not* experience placement instability, who constitute a larger proportion of the Florida sample. Similar to the approach we applied to Tennessee, we also tuned the model to increase sensitivity relative to specificity. This required setting a relatively low cut point in order to increase the number of children predicted to experience placement instability. The cut point for the predicted probability for Florida was 0.05 (we discuss the technical details of this process in Appendix E). It should be reemphasized here, however, that the choice of cut point used to predict whether children experience placement instability is ultimately a policy decision. If child welfare agencies determine that correct identification of children who experience superutilization is more important than correctly identifying non-superutilizers, then a lower cut point should be used. In turn, this increases sensitivity relative to specificity. The results reported in VIII.8 below reflect this decision.

An implication of this decision, however, is that the PPV is likely to be lower while the NPV will be higher. Again, the results reported in VIII.8 are consistent with this expectation. Specifically, the PPV indicates that, among those children who are predicted to experience placement instability, approximately 30 percent actually did so (i.e., were true positives). By contrast, the NPV indicates that, among children predicted *not* to experience placement instability, approximately 92 percent did not do so (i.e., were true negatives).

Overall, the RF model for Florida appears to identify children who experience placement instability and those who do not with a reasonable degree of classification accuracy, despite a different underlying model specification than that used for Tennessee.

VIII.8. Florida: RF model's predictive performance with the test sample

AUC	Accuracy	Sensitivity	Specificity	PPV	NPV
0.722	0.750	0.589	0.777	0.304	0.919

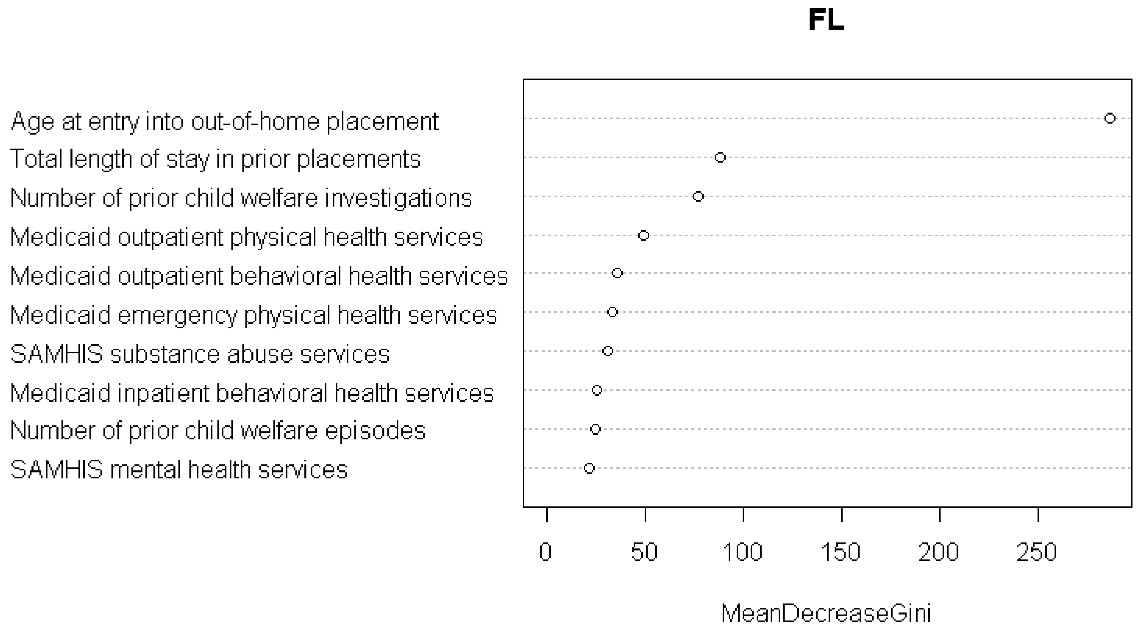
Source: Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

Note: N= 2,487. **AUC** = area under the ROC curve; **accuracy** = (prevalence)*sensitivity + (1-prevalence)*specificity; **sensitivity** = true positive rate of superutilization; **specificity** = true negative rate of nonsuperutilization; **PPV** = positive predictive value, or the probability that children classified as superutilizers truly are superutilizers; **NPV** = negative predictive value, or the probability that children classified as nonsuperutilizers are truly nonsuperutilizers.

b. Interpreting variable importance

To answer the research question about which characteristics predict superutilization in Florida, we again used variable importance and partial dependence plots. Figure VIII.5 lists the 10 most important variables in the Florida model in terms of mean decrease in the Gini index. Similar to the results for Tennessee, a child's age at entry into out-of-home placement was the most important predictor by a wide margin.

Figure VIII.5. Ten most important predictors of placement instability superutilization in Florida



Source: Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

Figure VIII.6 lists the 10 most important predictors based on the mean change in the Gini index. The layout of the plots is the same as that used for Tennessee, with the most important variables listed from top to bottom, left to right.

Similar to Tennessee, the most important predictor for placement instability in Florida is a child's age at entry into the first out-of-home placement in the prediction period. And as in Tennessee, the predicted probability of experiencing placement instability in Florida increase notably between ages 11 and 12. The marginal probability changes from less than 0.10 at age 11 to roughly 0.18 at age 12. At subsequent ages, the probability increases steadily, with another jump between ages 13 and 14. The probability of placement instability is highest for children who are 17 when entering custody. The general result relating age to superutilization appears to be robust across both sites in our study.

The second most important variable is the length of time spent in prior out-of-home foster care. Although the marginal change in predicted probability of superutilization is not particularly large (from about 0.10, with no time spent in prior out-of-home foster care, to roughly 0.14 after

1,000 days spent in foster care), overall it does suggest that a child's history in the child welfare system may be worth considering when identifying children at higher risk of superutilization.

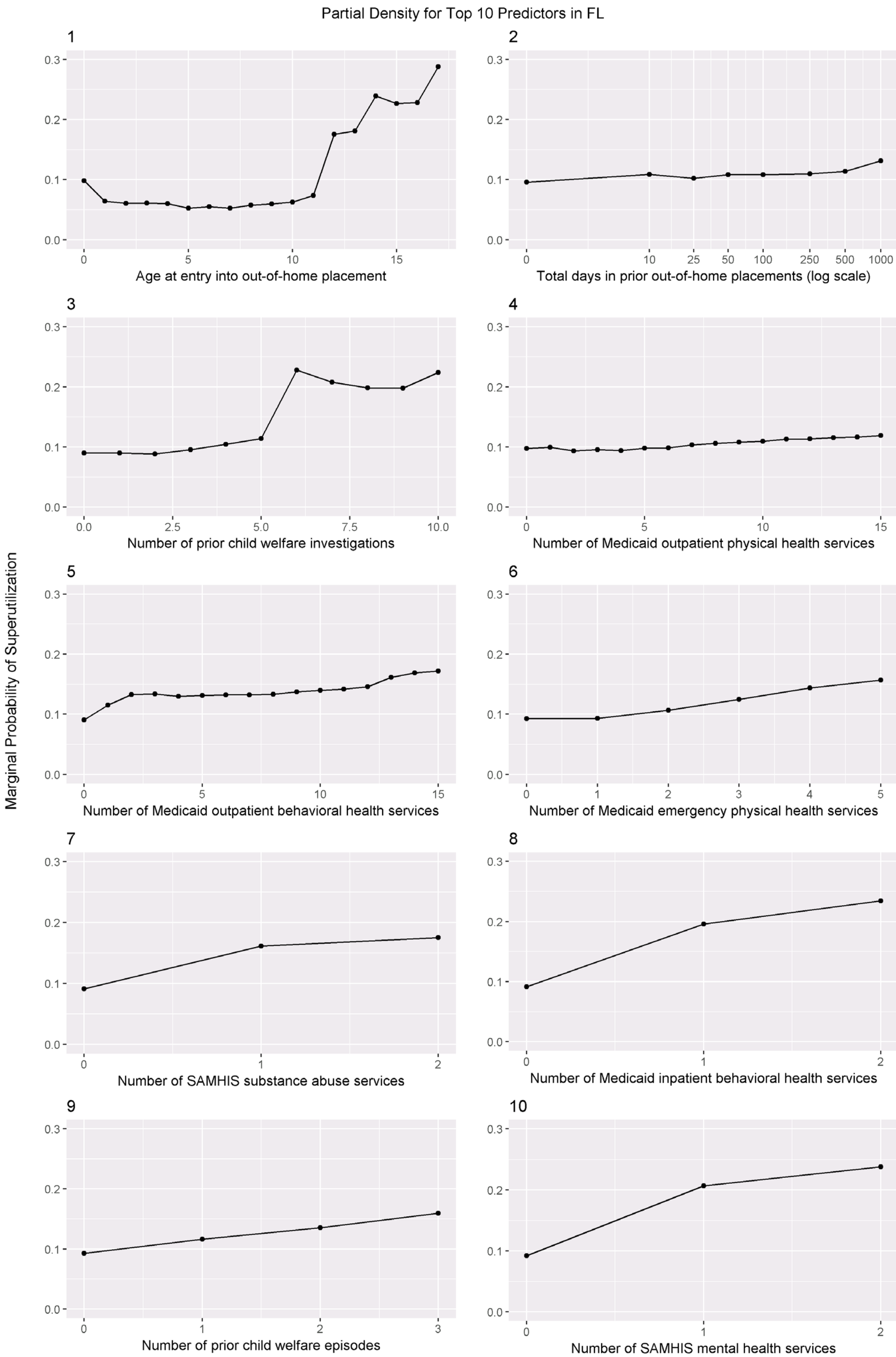
The third most important variable, the number of prior child welfare investigations, may also be useful for child welfare agencies. The predicted probability of superutilization doubles—from about 0.10 to a little more than 0.20—after five investigations before leveling off with additional investigations. This suggests that tracking prior investigations could be part of an early warning system for placement instability. A similar case could be made for the prior number of child welfare episodes (the ninth most important variable). As the number of prior episodes increases, the predicted probability of superutilization also increases. This suggests that a child's episode history could indicate his or her future risk for experiencing placement instability.

The fourth, fifth, sixth, and eighth most important variables involve Medicaid service receipt during the lookback year. In particular, the number of outpatient physical health services received via Medicaid appears to have a relatively small impact on the probability of placement instability which increases slightly after 10 services in the lookback period; despite this smaller impact, it is still identified as an important variable. It is also possible that this variable may be impacted by other variables in the model in ways that are not yet well understood (that is, they potentially interact with others in the RF model in a way that increases the predicted probability but is not easily detected by plotting the marginal probability on only the variable itself). Examining these dynamics may be of interest for future work.

In contrast to this relationship, the number of outpatient behavioral health services received via Medicaid during the lookback period slightly increases the chances of placement instability. Likewise, receiving emergency physical health services via Medicaid has a marginal (but more noticeable) impact on the baseline probability of superutilization—which rises from 0.10 to 0.15 when a child has received five prior emergency services. Finally, receiving one inpatient behavioral health service via Medicaid during the lookback period doubles the predicted probability of placement instability in the t0 episode. Taken together, these results suggest that it may be useful to share and incorporate Medicaid service data into early warning systems for child welfare and comprehensive health histories should be included in any assessments or records at the time of entry into foster care.

Another important variable is the use of SAMH substance abuse and mental health services during the lookback period, the 7th and 10th most important variables, respectively. If a child receives one non-Medicaid substance abuse service, his or her predicted probability of placement instability increases from 0.10 to 0.15—a 50 percent increase. Similarly, if a child receives one non-Medicaid mental health service in the lookback period (vs. not receiving any services), his or her predicted probability of placement instability doubles from roughly 0.10 to 0.20. The predicted probability increases to roughly 0.25 with the receipt of two mental health services in the lookback period. Again, this suggests that it may be worthwhile to share and integrate assessments and data on substance abuse services into an early monitoring system for child welfare. It would be very useful to understand the factors at play when a child is receiving these non-Medicaid services for which they should be otherwise eligible, as they play a role in predicting placement stability.

Figure VIII.6. Florida: Ten most important predictors of superutilization based on placement moves



Source: Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

3. Children who did not experience placement instability despite a high probability

As discussed previously, our models achieved strong classification performance, meaning that we were able to accurately distinguish children who experience superutilization from those who do not. But, as with all predictive models, some children were misclassified. The two basic types of misclassification related to this research question were false negatives (children predicted to not experience placement instability but who actually did) and false positives (children predicted to experience placement instability but who actually did not). This section discusses this second type of misclassification - children who do not experience placement instability despite having a high predicted probability.

Both study sites had false positives. In Tennessee, 2,870 children (23.8 percent of the sample) were incorrectly classified as experiencing placement instability, as were 1,743 children (21.0 percent of the sample) in Florida. Children misclassified in this way have predicted probabilities for placement instability that are high enough to consider them to be at risk for superutilization based on the model and our selected cut points, but the children do not experience placement instability.

There are several potential reasons for this misclassification. First, we believe that the most likely possibility is that there are factors influencing superutilization that we did not directly observe and could not include as predictors. For example, we did not have data related to the quality of the out-of-home placement during the t0 episode. Some of these factors may be less tangible or directly measurable, such as being placed into a nurturing environment, but are nonetheless important in determining a child’s risk for superutilization. To capture less tangible concepts, we might need alternative data that are better geared toward measuring these factors, such as survey or observational data on the quality of the placement. However, this was outside the scope of our effort.

Another possibility is that our predictive model is not accurately reflecting the relationship between our set of predictors and the probability of experiencing placement instability. However, we believe this is unlikely. Our modeling technique—the RF—is designed to be flexible in that it can capture the important relationships in the data with minimal assumptions imposed a priori and without overfitting the data. This means that the model should perform nearly as well on an external data set as it does on the data we used to fit the model. This contrasts with a simpler logistic regression model, which makes much stronger assumptions about the relationship between predictors and the probability of placement instability. In addition, the strategy we used to split our sample between training and test sets and our use of cross-validation to optimize tuning parameters (see Appendix E) should minimize the effect of model limitations on misclassification.

Finally, another important reason for the relatively high rate of false positives is that we designed our classification effort to be more inclusive regarding which children were predicted to experience placement instability. As discussed in Appendix E, the RF model generates a predicted probability of superutilization for all children, after which we chose a cut point for this probability. Children whose probability exceeded this cut point were predicted to experience placement instability. A naïve approach would have been to use 0.5 as the default cut point, but doing so would have resulted in identifying very few children at high risk for placement instability—which would have reduced the true positive rate as well as the false positive rate.

The main reason for this is that experiencing high degrees of placement instability is fairly rare (affecting 20 percent of the Tennessee sample and 14 percent of the Florida sample). To maximize the utility of our model for child welfare agencies, we considered it more important to be inclusive in identifying children at high risk for instability, and so we consciously chose a method that lowered the threshold for the predicted probability.

To fully answer questions about why some children with high predicted probabilities do not experience superutilization, we need to look beyond the data included in this study. Because our model already uses the full array of information available, any additional comparisons between true positives and false positives is essentially a restatement of the key model results. Instead, what is needed is a causal research design that uses new data. A causal study is beyond the scope of the current effort, but we can still provide initial thoughts on the best way to address this question in future work.

The most appropriate strategy is to design a causal study that can move beyond the suggestive findings of our predictive model. A causal study should also incorporate a mechanism for examining different pathways through which children may or may not experience superutilization. To accomplish this, an appropriate research design is required. Such a design would likely require access to the same data on child welfare investigations, placements, and services that we used in this study. It should also be structured in a way that allows for the modeling of different service use trajectories based on an established baseline risk of experiencing superutilization.

F. Conclusion

The LCA results described in this report identified distinct groups of children who met the superutilization threshold, which informed our discussions with the study partners in each state. One LCA group in each state was composed of children with many placement changes. This "superutilization group" had particular significance for the states, as they have other efforts under way to address the phenomenon more deeply. Based on the results of our latent class analysis for placement instability, each site chose to address the following questions:

- Although these children are receiving behavioral services, what is causing the frequent placement moves?
- What actions could be taken to address those factors, such as a change in the composition, sequencing, or intensity of child welfare, behavioral health, or other services?
- Are the children not receiving the counseling for attachment disorder or anger management necessary for them to heal and function so that they can stay in one placement until achieving legal permanency?
- What underlying conditions need to be better addressed?

Thus, each site selected placement instability as the basis for the predictive analysis, with an eye toward putting preventative measures in place to lower the number of youth experiencing placement instability and to curb the number of moves. The results of this analysis are key to understanding the factors that lead to a high risk of placement instability—and spotting them early enough to provide at-risk youth with the support and attention they need.

Many variables in the predictive model have an expected effect on the likelihood of placement changes, such as older children and a prior number of investigations. As children age, they will be more likely to have placement changes, in part, as a function of time. Similarly, we would expect the total length of stay in foster care to be associated with placement instability due to the issue of more time for more placement moves, though this does not necessarily have to be the case.

For both sites, prior child welfare investigations predict placement instability. This finding may indicate that at the time of investigation, many families' needs are not being addressed adequately enough. The point of investigation is a window of opportunity to assess family need and provide associated supports to prevent further involvement in the child welfare system. Some of the prior referrals are not being addressed well enough. As a result, if the initial agency response is not sufficient, these children are re-reported to CPS and eventually often taken into custody.

In addition, the predictive analysis results from Tennessee show that when child behavior problems are listed as a reason for removal, the child becomes much more likely to experience placement instability. This finding points to the importance of early invention in behavioral health, with the right intensity to address the child's needs and reduce placement disruption. In addition, efforts need to be taken on the system level to ensure that the behavioral health system provides the right levels of availability, access, and quality.

Medicaid services were also shown as important predictive factors for placement moves. Medicaid emergency room visits for physical health problems was a predictor in both sites, but questions remain about the nature of the relationship. One possibility is that emergency room visits are the result of—not the cause of—placement changes. This dynamic was documented in a study by Rubin et al. (2004), which found that children of all ages in the sample became increasingly reliant on emergency room ambulatory care services as the number of placements increased. Indeed, the rates of emergency service use more than doubled for all age groups beyond infancy.

Besides emergency services, Medicaid outpatient services for physical and behavioral services were predictive factors for both sites. In Tennessee, we found a fairly sharp uptick in outpatient behavioral health services funded by Medicaid during the lookback period—from zero to three services. This variable was the second most powerful predictor based on the Gini index. It may mean that children requiring more of these services have comorbid conditions (multiple behavioral health problems) or more severe behavioral health problems.

These variables could be incorporated into an alert system that flags children who might benefit from wraparound services or more intense case management or treatment, with the goal of meeting their physical and behavioral needs so that they do not experience superutilization. Providers could be trained on the unique developmental needs of youth in foster care and coordinate more closely with caseworkers and foster parents on how best to meet their needs and improve their health outcomes to promote placement stability.

For Florida, the inclusion of SAMH-funded substance abuse and mental health services were also important predictors of placement instability. SAMH services could be used if a child's need was judged to be not medically necessary or if a Medicaid provider was not available. This raises the question of whether service gaps in the Medicaid and child welfare delivery systems are causing delays in treatment and greater difficulties for some children—making them more likely to experience placement instability and superutilization. The criteria for medical necessity could be re-examined. Also, if children are receiving SAMH services because of a lack of available Medicaid providers, which one site reported, a gap analysis on population needs and services needs to be conducted and incentive structures set up to close that gap. Finally, further information could also provide insight regarding whether there is a delay in service receipt due to Medicaid denial or lack of availability that is unnecessarily affecting children's well-being in a way that leads to greater placement stability.

For youth in some homes, the support for the foster parents or the behavioral health services being provided are insufficient to help children function well. More investment in finding the right foster home—and more caregiver training, support, and coaching for a child's behavioral or physical health needs when they are identified—would go a long way to help prevent placement changes, decrease foster parent stress, and improve children's well-being.

In addition to practice and policy implications, there are several implications related to further development and use of predictive analysis to help various service agencies. For example, this study has shown that it is possible to construct predictive models that reasonably accurately differentiate children who experience placement instability from those who do not. We believe this finding contributes to the growing potential to develop predictive analytic models to inform case management and service provision for child welfare, Medicaid, and other agencies for other key outcomes – like duration in care, use of residential treatment, etc.

Moreover, our results show that it is possible to develop robust models capable of predicting placement instability (and possibly other types of superutilization) by building on data systems that states may already have available. In addition, variables derived from diverse sources, such as child welfare investigations, Medicaid, and substance abuse and mental health agencies, were important predictors in our study. This demonstrates the need to share and use data across agencies to inform policy- and case-level decision making.

IX. CONCLUSION

This chapter highlights key findings regarding superutilization of child welfare and other services and suggests possible implications. When reviewing these findings, it is important to note that we do not place a value on superutilization. We want to caution readers not to interpret high levels of service use as necessarily a negative outcome. Many children have complex physical and behavioral health needs that warrant high levels of outpatient and inpatient services, for example. Our findings do not attempt to make claims about the appropriate levels of service use. Rather, we simply identify high levels of service use to help child welfare, Medicaid, and other agencies learn more about those experiencing superutilization, and to identify opportunities to improve efficient and effective service provision.

This chapter begins with an overview of key findings and implications to inform policy and practice, promoting improved service provision and better outcomes for children and families in the child welfare system. Next, we discuss study limitations to consider when interpreting results. The chapter concludes with considerations for future research.

A. Findings and implications

The study addresses research questions to provide much-needed insights into superutilization of services among children and families in the child welfare system. The use of cross-system linked administrative data from child welfare and Medicaid in both sites, along with other substance abuse and mental health services in Florida, provided a rich set of data on service use for children in the child welfare system. The descriptive analysis alone, providing a description of superutilization of child welfare, Medicaid and other services, contributed much needed knowledge on system engagement, functioning, and service provision for children in foster care. Applying advanced methods, specifically latent class and predictive analysis, allowed us to answer nuanced questions about specific types of superutilization and what factors may be predictive of superutilization.

As findings were shared with project and site partners, we identified several implications for policy and practice. Several key implications are summarized below but should not be considered an exhaustive list. Rather, it should serve as a starting point for further discussion between the study partners and those in the field.

1. Cross-system service use

The descriptive, latent class, and predictive findings regarding services use among children in foster care provides a valuable contribution to the literature and the field to provide insights regarding child welfare, Medicaid and other service use. Site partners were interested in learning about the extent to which children in child welfare used Medicaid and other services, given that this information is typically not shared across agencies. The information learned from analyzing linked data across systems demonstrates the important of cross system information and leveraging opportunities to share data to inform policy and practice. This point is reinforced throughout the study with important findings regarding use of Medicaid services and other substance use and mental health services when identifying types of superutilization and predictive factors of placement instability. A key implication for child welfare and Medicaid agencies is to build relationships and share data across systems, so that they have holistic information about cross-system services to make informed decisions, engage in a coordinated, tailored approach to providing services, and efficiently use limited resources.

2. Measuring superutilization

As discussed in Chapter V, we developed a multifaceted measure of superutilization that leveraged the rich services data shared by our site partners. This study looked beyond using only cost to measure superutilization and used several measures capturing the nuance of service provision, such as frequency, duration, and intensity. Based on feedback from our site partners, this nuance was important for them to understand how to conceptualize superutilization and consider specific service or policy interventions to address the needs of those experiencing superutilization. By having specific information about the type or frequency of a service, rather than just cost, to identify superutilization, child welfare and Medicaid agencies have a more specific understanding of how those children or families are experiencing superutilization.

3. Types of superutilization

An important finding and implication for policy and practice among child welfare, Medicaid, and other service agencies is that there are multiple distinct types of superutilization. These types differed on several key domains, especially type of service use, which further emphasizes the importance of having a holistic understanding of service use across systems when making decisions regarding service provision for children and families. Based on discussions with site partners, identifying seven classes of superutilization in Tennessee and eight classes of superutilization in Florida allowed them to take a more nuanced look at children experiencing high levels of service use. They were able to consider the specific needs and actions that could be taken to improve services and outcomes for each type. Also, because most of the classes were similar across sites, we can start to hypothesize some common types of superutilization that may be present across jurisdictions and can inform the extent to which this research can be generalizable.

One type of superutilization of interest to both sites was the group experiencing a high number of placement moves. Site partners noted their challenges with placement instability in particular and wanted to know more about how to better meet the needs of these children. Although some placement moves can be positive, such as moving a child from a more restrictive residential setting to a relative placement, efforts are needed to reduce placement instability given the disruption it causes for the child in regard to continuity of services, recovering from trauma, and building relationships with caring adults. These research results can be used by child welfare agency administrators to focus their attention on the group of children experiencing a high number of placement moves to further assess their needs and understand placement instability to try and prevent moves that maybe harmful or preventable.

4. Predicting placement instability

Partners from both sites wanted to focus on the high number of placement moves as the particular type of superutilization for the predictive analysis. The analysis results identified several important predictors of placement instability, specifically prior child welfare involvement (prior investigations and episodes, and time in prior episodes), Medicaid service use (outpatient services for physical and behavioral health, inpatient behavioral services, and emergency services for physical health), and SAMH (substance use and mental health services). These predictive factors are cross-system and demonstrate the importance of a more holistic view of child welfare, Medicaid, and other services to assess and engage children and families in the child welfare system. The predictive results inform several possible policy and practice implications to address placement instability include:

- Improve foster parent recruitment, retention, and support in order to care for children with behavioral health needs
- When a family comes to the attention of child welfare, use engagement efforts as a real opportunity to prevent further child welfare involvement—with the right intensity and type of services
- Consider ways to engage Medicaid providers in treatment plans for youth in foster care
- Use predictor variables as a flag in the administrative data system to have further case consultation
- Consider a case record review process of youth on their way to experiencing high placement stability based on their predictive characteristics
- Implement early, targeted intervention based on predictive characteristics
- Conduct behavioral health screening for all young children entering foster care
- Engage mental health and early childhood consultants on staff in child welfare agencies
- Closely examine the quality and type of behavioral health services being paid by Medicaid, including whether they are evidence-based and how outcomes are being tracked at the state level specifically for youth in foster care
- With federal approval, Medicaid may be an avenue for reimbursing evidence-based practices, thereby offsetting some of their costs at the state level; this can be done through a state plan amendment, waivers, or pre-existing reimbursement structures[14]

B. Limitations

As with any study, there are several limitations for readers to keep in mind when interpreting the results and drawing conclusions. In particular, our conceptualization of superutilization identified high services users but does not explicitly address the issue of whether high levels of service utilization are appropriate for the level of need.

Also, the data sources are limited to the population of children entering foster care during specific time periods for two sites—the state of Tennessee and the three-county area of Hillsborough, Pinellas, and Pasco, Florida. In some states, the youth in out of home care includes those placed in foster homes and institutions for juvenile justice supervision. For this study, juvenile justice youth were not included in these analyses. Although these results may be informative for other states and localities, caution should be used when applying the results and insights from this study to other jurisdictions or time periods. For example, there may be specific

[14] See http://www.cebc4cw.org/files/CEBCMedicaidReimbursementToSupportTheUseOfEBPs.pdf for more information.

programs or policy contextual factors that occurred during the study time period in these sites, which may be an unmeasured influence on the results. Nonetheless, the similarities of the results across sites, lead to more confidence in generalizing these results to other jurisdictions or guiding their own individual analyses.

The availability of data also limited our study scope. In particular, we focused our study on services linked to the child in the administrative data from site partners. We requested and assessed the available data on parents but given limitations with these data, we were not able to include services linked to parent records. Also, limited availability of Eckerd services data during the study window led to a reduced time frame for the descriptive and latent class analysis in which we included these data. Also, detailed information on CBC-purchased child welfare services and costs were minimal for the Florida sample.

In addition, to maximize the use of available administrative data for the descriptive and latent class analysis, we did not construct cohort time periods in which to assess children's services over a set period of time. Although this would have allowed for consistency in comparison, it would have reduced our sample for analysis. However, to help address variability in which children were part of the study time frame, we constructed rate measures to standardize measures of services.

While the analysis focused on data that child welfare caseworkers are likely to have access to, as with any study, we are limited to only those variables for which we have data and have included in the analysis. There may be other important factors to consider that were not available in the data for the study. For example, cost data was unavailable or limited for several services of interest, including placement costs for Florida. Also, child assessment data were not universally available or assessment scores were limited to a total score, such as with the CANS assessment in Tennessee. System performance variables that would affect children's outcomes were also beyond the scope of this study (e.g., worker turnover and caseload size.)

Although the results provide potentially important insights into understanding various types of superutilization and the factors that help predict placement instability in particular, these findings do not indicate causal relationships. The descriptive and the predictive analysis results should not be misinterpreted or used in any way to conclude causality for superutilization.

It is also important to point out that our descriptive analysis of different types of superutilization discussed in Chapter VII is based on a relatively simple latent class model. Although this simplicity is preferable given the exploratory nature of the analysis at this first stage of trying to understand superutilization, a more complex model that includes additional measures and covariates may be preferable in the future. One reason for this is that, as work continues in this area, our collective understanding of the dynamics and contextual factors that influence different types of superutilization may grow. As this understanding expands, the latent class models provided in this study should be revisited and refined to incorporate new insights and findings. It is therefore important not to reify our latent class results but to view them as a starting point for gaining a better sense of an important phenomenon—one that is likely dynamic and may not manifest itself the same way in other contexts over time.

Similarly, our predictive results should be seen as a starting point regarding the ability of child welfare, Medicaid, or other agencies to use information that should be available to them to identify children who may be at risk for superutilization. Although our results suggest that well-performing predictive models can be developed for children at risk for placement instability, further refinement may be possible with additional information. Moreover, as discussed in Chapter VIII, we made a decision based on policy considerations to maximize certain predictive components of the model, such as sensitivity—that is, to maximize our ability to identify children who truly experienced superutilization. However, depending on the policy context, a child welfare agency may prefer to focus instead on correctly predicting children who are *not* likely to experience superutilization—that is, to maximize specificity. Thus, agencies may choose to design predictive models with different preferences in mind.

Also, our measurement of Medicaid services for this study was somewhat different from other studies leveraging Medicaid data. In particular, we used Medicaid services data without including Medicaid eligibility information. Given the categorical eligibility for Medicaid among those in foster care, we did not create service measures based on Medicaid eligibility data, which would have required extensive resources and data management. However, our measures of Medicaid service use for our superutilization outcome measures are focused on the time period children are in foster care, making them categorically eligible. For the predictive analysis, particularly for the lookback period before entry into child welfare custody, we are uncertain about their Medicaid eligibility or use of other healthcare services they may have received during that time period. Therefore, we are cautious throughout the report to focus our discussion on Medicaid service use and do not make claims about overall use of healthcare services or Medicaid eligibility, given Medicaid eligibility is uncertain during periods in which children may not have been in foster care.

C. Future research

Our findings help answer the key research questions and provide important implications for policy and practice. But they also have implications for future research. Central to this study was the ability to access and link cross-system administrative data from child welfare, Medicaid, and other services. Future research is needed to scrutinize service provisions across systems to obtain a more holistic view of services received by children and families.

This study also provides valuable insights into the nuances of superutilization of services. Future research should consider measures of service superutilization that look at factors beyond cost, given that data about type, duration, frequency, and intensity are informative and even necessary to translate findings into recommendations for policy or practice. Also, future descriptive studies that continue to assess superutilization should also include study of the timing and sequencing of services to examine different pathways through which children may experience superutilization. Furthermore, additional research can provide insights into the impact of superutilization on children's well-being.

Our predictive analysis focused on one type of superutilization—the number of placement moves. These predictive results may not apply to other forms of superutilization, such as those which experience multiple custody episodes, long durations in foster care, high use of group or residential care, or high use of Medicaid emergency services. In fact, there is no guarantee that the reasonably strong performance for predicting high numbers of placement moves will transfer to other forms of superutilization, which may have more complex antecedents and affect fewer children in the child welfare system. Thus, our predictive results should only be viewed as suggesting that it's possible to predict a specific type of superutilization. However, it remains an open question as to how other forms of superutilization may be predicted, and more research is needed to identify predictive factors associated with other types of superutilization.

Lastly, although we briefly discussed in the prior chapter those children with a high predictive likelihood yet do not experience superutilization in regard to placement moves, future research with a causal study design is needed to understand what might explain this. Future research using a randomized control trial or quasi-experimental design, such as propensity score matching, could be used to test interventions that could prevent placement instability.

REFERENCES

Allen, K. and T. Hendricks. *Medicaid and Children in Foster Care*. State Policy Advocacy and Reform Center, 2013.

Altman, N.S. "An Introduction to Kernel and Nearest-Neighbor Nonparametric Regression." *The American Statistician,* vol. 46, no. 3, 1992, pp. 175–185.

Billings, J., and. T. Mijanovich. "Improving the Management of Care for High-Cost D.2 Patients." *Health Affairs (Project Hope),* vol. 26, no. 6, 2007, pp. 1643–1654.

Breiman, Leo "Random Forests." *Machine Learning*, vol. 45, no. 1, 2001, pp. 5–32.

Bright, C. L., and M. Jonson-Reid. "Multiple Service System Involvement and Later Offending Behavior: Implications for Prevention and Early Intervention." *American Journal of Public Health*, vol. 105, no. 7, 2015, pp. 1358–1364. Available at http://doi.org/10.2105/AJPH.2014.302508. Accessed November 29, 2017.

Bronfenbrenner, U. and P.A. Morris. "The ecology of developmental processes." edited by W. Damon. Handbook of Child Psychology. New York: John Wiley & Sons, 1998, pp. 993-1028.

Bronfenbrenner, U. *The Ecology of Human Development*. Cambridge, MA: Harvard University Press, 1979.

Celeux, G., and G. Soromenho. "An Entropy Criterion for Assessing the Number of Clusters in a Mixture Model." *Journal of Classification,* vol. 13, no. 2, 1996, pp. 195–212.

Clark, C. and S. Yampolskaya. *Mental health services expenditures among children placed in out-of-home care.* Administration and Policy in Mental Health, vol 38, 2011, pp. 430-439.

Collins, L.M., and S.T. Lanza. *Latent Class and Latent Transition Analysis: With Applications in The Social, Behavioral, and Health Sciences.* John Wiley & Sons, 2013.

Gu, L., R. Baxter, D. Vickers, and C. Rainsford. "Record Linkage: Current Practice and Future Directions." CSIRO Mathematical and Information Sciences Technical Report, vol. 3, 2003, p. 83.

Hallquist, M., and J. Wiley. "MplusAutomation: Automating Mplus Model Estimation and Interpretation." R Package Version 0.6, 2011. Available at http://cran.r-Project.org/web/packages/MplusAutomation/index.html.

Hanley, James A., and Barbara J. McNeil. "A Method of Comparing the Areas Under Receiver Operating Characteristic Curves Derived from the Same Cases." *Radiology*, vol. 148, no. 3, 1983, pp. 839–843. DOI:10.1148/radiology.148.3.6878708. PMID 6878708.

Hastie, T., R. Tibshirani, and J. Friedman, J. *The Elements of Statistical Learning.* New York: Springer New York Inc., 2001.

Jagannathan, R. and M. Camasso. "Social Outrage and Organizational Behavior: A National Study Of Child Protective Service Decisions." *Children and Youth Services Review,* vol. 77, 2017, pp.159-163.

James G., D. Witten, T. Hastie, R. Tibshriani. An Introduction to Statistical Learning. . New York: Springer New York Inc., 2013.

Jerome Friedman, Trevor Hastie, Robert Tibshirani. "Regularization Paths for Generalized Linear Models via Coordinate Descent." *Journal of Statistical Software*, vol. 33 no. 1, 2010, pp. 1–22. Available at http://www.jstatsoft.org/v33/i01/. Accessed November 29, 2017.

Kranker, K., S. O'Neil, V. Oddo, M. Drapkin, and M. Rosenbach. "Strategies for Using Vital Records to Measure Quality of Care in Medicaid and CHIP Programs." Centers for Medicare & Medicaid Services Medicaid/CHIP Health Care Quality Measures, Technical Assistance Brief no. 4, January 2014. Available at http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-Topics/Quality-of-Care/Maternal-and-Infant-Health-Care-Quality.html.

Landsverk, J., I. Davis, A. Garland, R. Hough, A. Litrownik, and J. Price "*A Developmental Framework for Research with Victims of Child Maltreatment Placed in Foster Care."* San Diego, CA: Center for Research on Child and Adolescent Mental Health Services, Children's Hospital, 1995.

Leininger, L.J., B. Saloner, and L.R. Wherry. "Predicting High-Cost Pediatric Patients: Derivation and Validation of a Population-Based Model." *Medical Care*, vol. 53, no. 8, 2015, pp. 729–735.

Leininger, L.J., D. Friedsam, K. Voskuil, and T. DeLeire. "Predicting High-Need Cases Among New Medicaid Enrollees." *The American Journal of Managed Care,* vol. 20, no. 9, 2014, pp. e399–407.

Liaw, A., and M. Wiener. "Classification and Regression by Random Forest." *R News,* vol. 2, no. 3, 2002, pp.18–22.

Linzer, D.A., and J.B. Lewis. "poLCA: An R Package for Polytomous Variable Latent Class Analysis." *Journal of Statistical Software,* vol. 42, no. 10, 2011, pp. 1–29.

Loman, L.A. *Families frequently encountered by child protection services: A report on chronic child abuse and neglect.* Institute of Applied Research, 2006.

Maher, Erin, Elizabeth Weigensberg, Matthew Stagner, Jessica Nysenbaum, and Sarah LeBarron. "Addressing Unaddressed Needs: Helping Agencies Target Services to Children and Caregivers in Child Welfare." Issue Brief. Washington, DC: Mathematica Policy Research, December 2016.

Mancuso, D. *Improving service delivery for high need Medicaid clients in Washington State through Data Integration and Predictive Modeling*. Washington State Department of Social and Health Services, July 2015.

Marascuilo, L. A. "Large-sample multiple comparisons." *Psychological Bulletin*, vol. 65, no. 5, 1966, p. 280.

Max Kuhn. Contributions from Jed Wing, Steve Weston, Andre Williams, Chris Keefer, Allan Engelhardt, Tony Cooper, Zachary Mayer, Brenton Kenkel, the R Core Team, Michael Benesty, Reynald Lescarbeau, Andrew Ziem, Luca Scrucca, Yuan Tang, Can Candan and Tyler Hunt. "Caret: Classification and Regression Training." R Package version 6.0-76, 2017. Available at https://CRAN.R-project.org/package=caret. Accessed November 29, 2017.

Medicaid and CHIP Payment and Access Commission. "Behavioral Health in the Medicaid Program—People, Use, and Expenditures: Report to Congress on Medicaid and CHIP." Washington, DC: Medicaid and CHIP Payment and Access Commission, June 2015.

Mihaylova, B., A. Briggs, A, O'Hagan, and S.G. Thompson. "Review of Statistical Methods for Analyzing Healthcare Resources and Costs." *Health Economics,* vol. 20, no. 8, 2011, pp. 897–916.

Molitor, F., C. Lichtenstein, A.M. Stevenson, and P.J. Pecora. *Year Two Interim Evaluation Report for the California Residentially Based Services (RBS) Reform Project.* Walter R. McDonald and Associates and Casey Family Programs, 2012. Available at http://www.childsworld.ca.gov/PG2119.htm,

Muthén, L. *Mplus User's Guide.* Los Angeles: Muthén & Muthén*,* 2010.

Nagin, D. *Group-Based Modeling of Development.* Cambridge, Mass.: Harvard University Press, 2005.

Nylund, K.L., T. Asparouhov, and B.O. Muthen. "Deciding on the Number of Classes in Latent Class Analysis and Growth Mixture Modeling: A Monte Carlo Simulation Study." *Structural Equation Modeling*, vol. 14, no. 4, 2007, pp. 535–569.

Paxton, N., J. Galin, K. Kranker, and M.K. Fox. "FNS WIC—Medicaid Study II." State User's Guide. Washington, DC: Mathematica Policy Research, 2014.

Pecora, P.J., R.C. Kessler, J. Williams, A.C. Downs, D.J. English, J. White, and K. O'Brien. What Works in Family Foster Care? Key Components of Success from the Northwest Foster Care Alumni Study. New York and Oxford, England: Oxford University Press, 2010, p. 42.

R Core Team. "R: A Language and Environment for Statistical Computing." R Foundation for Statistical Computing, Vienna, Austria. Available at https://www.R-project.org/. Accessed November 29, 2017.

Rice, Marnie E., and Grant T. Harris. "Comparing Effect Sizes in Follow-Up Studies: ROC Area, Cohen's d, and r." *Law and Human Behavior*, vol. 29, no. 5, 2005, pp. 615–620.

Roberts, Y.H., O'Brien, K., Pecora, P.J. *Supporting Lifelong Families Ensuring Long-Lasting Permanency and Well-Being*. Casey Family Programs, 2017. Available at https://www.casey.org/supporting-lifelong-families/

Rubin, D.M., Alessandrini, E.A., Feudtner, C., Localio, A.R. & Hadley, T. (2004) Placement Changes and Emergency Department Visits in the First Year of Foster Care. *Pediatrics*. Vol. 114, pp.354-360.

Schliep, Klaus, and Klaus Hechenbichler "kknn: Weighted k-Nearest Neighbors." R package version 1.3.1. 2016. Available at https://CRAN.R-project.org/package=kknn. Accessed November 29, 2017.

Trout, A. L., Tyler, P. M., Stewart, M. C., & Epstein, M. H. (2012). On the way home: Program description and preliminary findings. Children and Youth Services Review, vol. 34, pp. 1115-1120. doi:10.1016/j.childyouth.2012.01.046

Twala, B., M.C. Jones, and D. Hand. "Good Methods for Coping with Missing Data in Decision Trees." *Pattern Recognition Letters*, vol. 29, 2008, pp. 950–956.

U.S. Census Bureau, American FactFinder. *2010 Census*. U.S. Census Bureau, 2010. Accessed on 10 March 2017.

U.S. Census Bureau, American FactFinder. 2011 – 2015 American Community Survey. U.S. Census Bureau's American Community Survey Office, 2015. Accessed on 10 March 2017.

U.S. Department of Health & Human Services, Administration for Children and Families, Youth and Families, Children's Bureau, 2017. *The AFCARS Report – Preliminary FY 2016 Estimates as of October 2017*. No. 24. Washington, D.C.: Author. Available at https://www.acf.hhs.gov/sites/default/files/cb/afcarsreport24.pdf

U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2018. *Child Maltreatment 2016.* Washington, D.C.: Author. Available at http://www.acf.hhs.gov/programs/cb/research-data-technology/statistics-research/child-maltreatment.

Urdapilleta, O., G. Kim, Y. Wang, J. Howard, R. Varghese, G. Waterman, S. Busam, and C. Palmisano. *National Evaluation of the Medicaid Demonstration Waiver Home and Community-Based Alternatives to Psychiatric Residential Treatment Facilities.* IMPAQ International for the Centers for Medicare & Medicaid Services, 2012.

Van Buuren, S., and Groothuis-Oudshoorn, K. "mice: Multivariate Imputation by Chained Equations in R." *Journal of Statistical Software*, vol. 45, no. 3, 2011, pp. 1–67.

Vermunt, J.K. "Latent Class Modeling with Covariates: Two Improved Three-Step Approaches." *Political Analysis*, vol. 18, no. 4, 2010, pp. 450–469.

Weir, S., G. Aweh, and R.E. Clark. "Case Selection for a Medicaid Chronic Care Management Program." *Health Care Financing Review,* vol. 30, no. 1, 2008, pp. 61–74.

Wherry, L.R., M.E. Burns, and L.J. Leininger. "Using Self-Reported Health Measures to Predict High-Need Cases Among Medicaid-Eligible Adults." *Health Services Research,* vol. 49, no. S2, 2014, 2147–2172.

Wildeman, C., N. Emanuel, and J.M. Leventhal. "The Prevalence of Confirmed Maltreatment Among US Children, 2004–2011." *JAMA Pediatrics*, vol. 168, 2014, pp. 706–713.

Wurpts, I. and C. Geiser. "Is adding more indicators to a latent class analysis beneficial or detrimental? Results of a Monte-Carlo study." Frontiers in Psychology, edited by Lihshing Leigh Wang. 2014.

Yoshikawa, H., J.L. Aber, and W. Beardsley. "The Effects of Poverty on the Mental, Emotional, and Behavioral Health of Children and Youth: Implications for Prevention." American Psychologist, vol. 67, no. 4, 2012, pp. 272–84. DOI: 10.1037/a0028015, page 276.

Zou, Hui, and Trevor Hastie. "Regularization and Variable Selection via the Elastic Net." *Journal of the Royal Statistical Society*, Series B, vol. 67, Part 2, 2005, pp. 301–320.

This page has been left blank for double-sided copying.

APPENDIX A

CHARACTERISTICS AND SERVICES OF THE STUDY SAMPLE

This page has been left blank for double-sided copying.

TABLES

This page has been left blank for double-sided copying.

Tables presented in Appendix A include supplemental information related to the description of the sample characteristics (discussed in Chapter III) and services received (discussed in Chapter IV).

A. Contextual factors

A.1. Demographic contextual factors by Tennessee DCS region

	HS diploma[a] (%)	Foreign born (%)	Married (%)	Poverty (%)	Unemployed[b] (%)	Urban (%)
DCS region						
Davidson	87.5	12.2	37.3	18.2	7.2	96.6
East Tennessee	81.6	2.5	53.5	19.4	9.7	42.2
Knox	90.3	5.0	46.7	16.0	6.5	89.1
Mid-Cumberland	90.4	5.5	57.9	10.9	6.7	72.3
Northeast	84.3	2.0	50.0	19.5	8.2	59.6
Northwest	82.9	1.8	51.0	19.0	9.5	33.3
Shelby	86.5	6.2	37.7	21.4	10.3	97.2
Smoky Mountain	83.4	3.6	53.3	17.7	8.6	50.9
South Central	82.3	2.9	52.0	18.0	8.7	34.0
Southwest	83.2	1.8	49.7	19.6	10.9	42.0
Tennessee Valley	84.6	4.1	49.4	17.8	8.9	68.0
Upper Cumberland	81.2	3.3	51.9	20.9	8.7	31.9

Source: American Community Survey, 2015; Census, 2010.

Note: A map of Tennessee DCS regions can be found via the following link: https://www.tn.gov/assets/entities/dcs/attachments/DCS_Regional_Map_June_2016.pdf.

[a]Percentage of population ages 18 and older who have a high school diploma or more

[b]Percentage of unemployed is among the population ages 16 and older in the civilian labor force.

A.2. Race and ethnicity contextual factors by Tennessee DCS region

	White (%)	Black (%)	Hispanic (%)	Asian (%)	American Indian/ Alaska Native (%)	Native Hawaiian/ Pacific Islander (%)	Two or more races (%)	Other (%)
DCS region								
Davidson	62.4	27.6	9.9	3.2	0.3	0.1	2.4	4.0
East Tennessee	95.0	2.2	2.9	0.6	0.3	0.0	1.6	0.3
Knox	85.7	9.1	3.8	2.0	0.3	0.1	2.0	0.9
Mid-Cumberland	83.7	10.2	5.9	2.2	0.3	0.1	2.2	1.2
Northeast	94.6	2.3	2.2	0.7	0.3	0.0	1.5	0.6
Northwest	86.9	9.9	2.9	0.4	0.3	0.0	1.8	0.8
Shelby	40.2	52.7	5.9	2.5	0.2	0.0	1.7	2.7
Smoky Mountain	93.9	2.2	4.5	0.7	0.3	0.0	1.8	1.2
South Central	88.7	5.9	4.1	0.6	0.3	0.0	3.0	1.5
Southwest	72.0	24.9	2.7	0.6	0.2	0.1	1.4	0.7
Tennessee Valley	82.9	12.6	4.4	1.4	0.2	0.0	2.1	0.8
Upper Cumberland	95.5	1.3	4.0	0.5	0.3	0.0	1.6	0.7

Source: American Community Survey, 2015; Census, 2010.

Note: A map of Tennessee DCS regions can be found via the following link: https://www.tn.gov/assets/entities/dcs/attachments/DCS_Regional_Map_June_2016.pdf.

A.3. Contextual factors by Florida counties

	Hillsborough County (%)	Pasco County (%)	Pinellas County (%)
High school diploma or equivalency[a]	87.5	88.0	90.0
Foreign born	15.8	9.4	11.6
Married	44.3	50.6	40.1
Living below the poverty line	17.0	14.0	14.4
Unemployed[b]	9.0	9.4	8.4
Urban	96.5	90.5	99.7
Households with children under 18	32.3	27.0	21.0
White	71.1	88.7	82.6
Hispanic	26.1	13.1	8.7
Black	16.6	5.1	10.3
Asian	3.7	2.3	3.2
American Indian/Alaskan Native	0.4	0.4	0.3
Native Hawaii/Pacific Islander	0.1	0.1	0.1
Two or more races	3.2	2.4	2.5
Other race	4.9	1.1	1.0
Household size (average)	2.6	2.5	2.3

Source: American Community Survey, 2015; Census, 2010.

[a]Percentage of population ages 18 and older who have at least a high school diploma or equivalency.

[b]Percentage of unemployed is among the population ages 16 and older in the civilian labor force.

B. Type of placements

A.4. Share of time spent in family foster care or group, institutional, or residential care

	Percentage of time spent in custody placement			
	Mean	Median	Minimum	Maximum
Tennessee				
Average share of time spent in custody by placement type:				
Family foster care	78.6	99.5	0.0	100.0
Group, institutional, or residential care	8.1	0.0	0.0	100.0
Number of children				**21,672**
Florida				
Average share of time spent in custody by placement type:				
Family foster care	68.7	77.1	0.0	100.0
Group, institutional, or residential care	5.8	0.0	0.0	100.0
Number of children				**6,695**

Source: Tennessee DCS data; Florida OCW data.

Note: The average share of time spent in custody by placement type is calculated as the ratio of days spent in a specific placement type over total days spent in custody for each child. Placements with missing start or end dates or missing placement type are excluded from the analysis. As a result, these estimates may underestimate time in each placement type.

Family foster care includes the following placement types: foster family home (non-relative), foster family home (relative), pre-adoptive home, and relative. Group, institutional, or residential care includes the following placement types: group home, institution, and residential treatment. The distribution is calculated across all children in custody, including children who were not in foster care/group care.

A.5. First foster care placement type

	Number of children	Percentage of children
Tennessee		
First placement type during first episode		
Foster home (non-relative)	13,695	63.2
Foster home (relative)[a]	3,583	16.5
Group home/congregate care	725	3.3
Institution	1,648	7.6
Pre-adoptive home	920	4.2
Runaway	262	1.2
Supervised independent living	0	0.0
Trial home visit[b]	334	1.5
Missing	505	2.3
Number of children		**21,672**
Florida		
First placement type during first episode		
Correctional placement	9	0.1
Foster home	1,926	28.8
Hospitalization	298	4.5
In-home placement	1,341	20.0
Medical, mental health, or emergency services	192	2.9
Other	21	0.3
Relative foster care	311	4.6
Group home/residential care	4	0.1
Visitation	2,100	31.4
Number of children		**6,695**

Source: Tennessee DCS data; Florida OCW data.

[a]Foster home (relative) placements include licensed and non-licensed relative homes.

[b]In Tennessee, a trial home visit is considered an in-home placement, but does necessarily mean the child is placed in the same home from which he or she was removed.

C. Assessments

A.6. Assessments for Tennessee sample

			Distribution				
	Number of children	Percentage of children	Mean	Standard deviation	Median	Minimum	Maximum
CANS	13,798	63.7					
Level 1	10,887	78.9	–	–	–	–	–
Level 2	2,231	16.2	–	–	–	–	–
Level 3	580	4.2	–	–	–	–	–
Level 4	100	0.7	–	–	–	–	–
FAST	10,798	49.8					
Low	7,608	70.5	–	–	–	–	–
Moderate	2,308	21.4	–	–	–	–	–
High	882	8.2	–	–	–	–	–
Ansell-Casey Life Skills[a]	4,627	21.4	36.0	33.5	28.4	1.0	100.0
YLS[b]	391	1.8	12.1	6.0	11.0	1.0	35.0
Number of children							**21,672**

Source: Tennessee DCS.

Note: For the Ansell-Casey Life Skills and Youth Life Skills (YLS) assessments, the n value is the number of children with any assessment.

[a]The scoring range for the Ansell-Casey Life Skills assessment is 0–100.

[b]The scoring range for the Youth Life Skills (YLS) assessment is 0–40.

A.7. Assessments for Florida sample

	Number of children	Percentage of children
OCW investigation risk level	3,157	47.2
Low (1 to <2)	60	1.9
Moderate (2 to <3)	843	26.7
High (3 to <4)	1,705	54.0
Very high (4)	549	17.4
FARS overall score	15	0.2
Low (1 to <2)	11	73.3
Medium (2 to <3)	4	26.7
High (3)	0	0.0
FARS security domains score	13	0.2
Low (1 to <2)	12	92.3
Medium (2 to <3)	1	7.7
High (3)	0	0.0
CFARS overall score	933	13.9
Low (1 to <2)	765	82.0
Medium (2 to <3)	168	18.0
High (3)	0	0.0
CFARS security domains score	933	13.9
Low (1 to <2)	837	89.7
Medium (2 to <3)	93	10.0
High (3)	3	0.3
ASAM recommended level of care[a]	152	2.3
Intervention (1 to <2)	53	34.9
Methadone/medication maintenance (2 to <3)	12	7.9
Outpatient detox (3 to <4)	9	5.9
Regular outpatient treatment (4 to <5)	39	25.7
Intensive outpatient/day treatment (5 to <6)	10	6.6
Residential detox (6 to <7)	23	15.1
Residential (7)	6	3.9
ASAM placement level of care [a]	152	2.3
Intervention (1 to <2)	49	32.2
Methadone/medication maintenance (2 to <3)	10	6.6
Outpatient detox (3 to <4)	8	5.3
Regular outpatient treatment (4 to <5)	47	30.9
Intensive outpatient/day treatment (5 to <6)	9	5.9
Residential detox (6 to <7)	23	15.1
Residential (7)	6	3.9
Number of children	**6,695**	

Source: Florida OCW; Florida SAMH.

Note: The n value is the number of children with any nonmissing assessment scores. For children in Florida who had more than one assessment record, the average score for the child was used for estimates.

[a]The American Society of Addiction Medicine (ASAM) score corresponds to category of recommended or actual care, ordered by intensity of care. The ASAM average score was used to allocate children to categories. Consequently, the average should be interpreted with caution, since an average score of 4 to <5 (regular outpatient treatment) may not contain any regular outpatient placements (for example, it could contain an equal number of outpatient detox and residential detox placements).

D. Child welfare services

A.8. Average number of child welfare services by type

		Distribution			
	Number of children	Mean	Median	Minimum	Maximum
Tennessee					
Average number of services received per child among children in custody	18,220	6	4	1	88
Among children receiving child welfare services (n = 18,220):					
Average number of custodial services received per child among children in custody	17,296	5	3	1	88
Average number of noncustodial services received per child among children in custody	5,269	3	2	1	34
Number of children	**21,672**				
Florida					
Average number of Community Based Care (CBC) purchased services received per child among children in custody	1,325	2.0	1.0	1.0	27.0
Among children receiving child welfare CBC-purchased services (n = 1,325):					
Average number of custodial services received per child among children in custody	1,183	1.9	1.0	1.0	27.0
Average number of noncustodial services received per child among children in custody	224	1.9	1.0	1.0	20.0
Number of children	**6,695**				

Source: Tennessee DCS data; Florida OCW data; Eckerd data.

Note: Child welfare services for Florida are the CBC-purchased services provided by Eckerd. Custodial services are defined as services that started while a custody episode was in progress. Non-custodial services are defined as services that started while a custody episode was not in progress. Children can receive both custodial and noncustodial services.

Distributions calculated across those receiving services.

A.9. Number of child welfare services received for those receiving services

	Number of children	Percentage of children
Tennessee:		
Number of all child welfare services received among children receiving services (n = 18,220)		
One service	3,353	18.4
Two services	2,795	15.3
Three or more services	12,072	66.3
Number of children	**21,672**	
Florida:		
Number of all child welfare CBC-purchased services received among children receiving services (n = 1,325)		
One service	798	60.2
Two services	265	20.0
Three or more services	262	19.8
Number of children	**6,695**	

Source: Tennessee DCS data; Florida OCW data; Eckerd data.

Note: Child welfare services for Florida are the CBC-purchased services provided by Eckerd.

This page has been left blank for double-sided copying.

APPENDIX B

MEASURES OF SUPERUTILIZATION

This page has been left blank for double-sided copying.

TABLES

This page has been left blank for double-sided copying.

This appendix provides details related to all measures considered for inclusion in the definition of superutilization for Tennessee and Florida, respectively. The final selection of measures chosen is summarized in Chapter V.

B.1. Tennessee superutilization measures

Measure	Definition	Treatment of missing values	Measurement specification
Child Welfare			
Total number of episodes	Total number of episodes over the life of the child	N/A	Age-adjusted
Total number of placement moves	Total number of placement moves over the life of the child	Missing placements are excluded from counts. If all placement information is missing, variable is set to missing.	Age-adjusted
Total episodes length of stay	Total number of days in out-of-home placements over the life of the child	N/A. Missing length of stay (LOS) information is excluded from the total.	Age-adjusted
Average share of time in group/congregate care	Share of days spent in group or congregate care among time spent in out-of-home placements over the life of the child	Missing if all placement information is missing; set to 0 if no group care placements. If any group/congregate placements have missing LOS, then the total time in group care for that placement assumes an LOS of 0 and is not set to missing. Only placements with nonmissing LOS values were used to calculate total LOS.	Age-adjusted
Child welfare services per year	Total count of child welfare service starts over the duration of time (in days) in which the child was in contact with the Child Welfare system[a]	N/A. Measure is set to 0 if child does not have services.	Rate
Total placement cost per year	Total cost of child welfare placements among episodes that started within the study window over total duration[b]	Missing if all placement costs are missing. Otherwise, rate includes placements with missing cost (this implicitly sets these costs to 0 since the time associated with these placements is in the denominator but the costs are not in the numerator). Set to 0 if child has no episodes.	Rate
Child welfare service cost per year	Total cost of child welfare services among services starting within the study window over total number of days in which the child was in contact with the Child Welfare system[a]	Missing if all service costs missing. Otherwise, rate includes services with missing cost (this implicitly sets these costs to 0 since the time during these services is in the denominator but the costs are not in the numerator). Set to 0 if child has no services.	Rate
Medicaid			
Medicaid inpatient per year	Total number of inpatient services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during study window[c]	N/A. Measure is set to 0 if child does not have any inpatient services.	Rate

Measure	Definition	Treatment of missing values	Measurement specification
Medicaid inpatient behavioral health per year[d]	Total number of behavioral health inpatient services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during study window[c]	N/A. Measure is set to 0 if child does not have any inpatient behavioral health services.	Rate
Medicaid inpatient physical health per year[d]	Total number of physical health inpatient services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any inpatient physical health services.	Rate
Medicaid outpatient per year	Total number of outpatient services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any outpatient services.	Rate
Medicaid outpatient behavioral health per year[d]	Total number of behavioral health outpatient services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any outpatient behavioral health services.	Rate
Medicaid outpatient physical health per year[d]	Total number of physical health outpatient services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any outpatient physical health services.	Rate
Medicaid emergency per year	Total number of services received in emergency departments that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any emergency services.	Rate
Medicaid emergency behavioral health per year[d]	Total number of behavioral health emergency services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any emergency behavioral health services.	Rate
Medicaid emergency physical health per year[d]	Total number of physical health emergency services that occurred during custody episodes that started during the study window over total duration in custody episodes that started during the study window[c]	N/A. Measure is set to 0 if child does not have any emergency health services.	Rate

Note: "N/A" indicates that there were no missing values for the specific measure.

[a]Contact duration is defined by the number of days between (1) the start date of the first service or custody episode within the study window and (2) the end date of the last service or custody episode that started in the study window. After calculating services per day of contact duration, services per year was calculated by converting the rate in days to years by multiplying by 365. For example, *Services per year* = service count/contact duration*365. When a duration was less than 7 days, we recoded these cases to have a duration of 7 days. This was done in order to include the information in our sample while also down-weighting the probability that a very short duration would make the case likely to be flagged for superutilization. The alternative would be to discard these cases altogether; however, we decided to err on the side of inclusiveness in our analysis. If services or episodes were right-censored, we considered them to end on the last day of the study window for the purposes of calculating contact duration. Service cost was not prorated for right-censored episodes so total service cost would correspond to total service starts.

[b]Contact duration is defined by the number of days between (1) the start date of the first custody episode starting in the study window and (2) the end date of the last custody episode starting in the study window. After calculating cost per day of contact duration, cost per year was calculated by converting the rate in days to years by multiplying by 365. For example, *Total placement cost per year* = total placement cost/contact duration*365. When a duration was less than 7 days, we recoded these cases to have a duration of 7 days. This was done in order to include the information in our sample while also down-weighting the probability that a very short duration would make the case likely to be flagged for superutilization. The alternative would be to discard these cases altogether; however, we decided to err on the side of inclusiveness in our analysis. If episodes were right-censored, we considered them to end on the last day of the study window for the purposes of calculating contact duration. Placement cost was pro-rated to exclude costs incurred after the end of the study window.

[c]If the episode was right-censored, we included it but considered it to end on the last day of the study window.

[d]Measure was omitted in analysis.

B.2. Florida superutilization measures

Measure	Definition	Treatment of missing values	Measurement specification
Child Welfare			
Total number of episodes	Total number of out-of-home episodes over the life of the child	N/A	Age-adjusted
Total number of placement moves	Total number of placement moves in episodes with at least one out-of-home placement over life of child	Missing values are excluded from counts. If all placement information is missing, variable is set to missing.	Age-adjusted
Out-of-home episode length of stay	Total number of days in out-of-home placements among all episodes over the life of the child	Missing length of stay (LOS) information is excluded from the total. If all placements have missing length of stay, measure is also missing.	Age-adjusted
Average share of time spent in group or residential care	Share of days spent in group or residential care among time spent in out-of-home placements over the life of the child	Missing if all placement information is missing; set to 0 if no group or residential placements. If any residential placements have missing LOS, then the total time in group or residential care for that placement assumes an LOS of 0 and is not set to missing. Only placements with nonmissing LOS values were used to calculate total LOS.	Age-adjusted
Child welfare CBC-purchased services per year	Total count of child welfare CBC-purchased services (Eckerd) starts over the duration of time (in days) in which the child was in contact with Eckerd[a]	N/A. Measure is set to 0 if child does not have detailed services.	Rate

Measure	Definition	Treatment of missing values	Measurement specification
Child welfare CBC-purchased service cost per year	Total cost of child welfare CBC-purchased services (Eckerd) among services starting within the study window over total number of days in which the child was in contact with Eckerd[a]	N/A. Measure is set to 0 if child does not have detailed services.	Rate
Substance Abuse and Mental Health			
Mental health services per year	Number of SAMH mental health treatment episodes occurring over the duration of mental health service receipt within the study window; measure includes left-censored services[c]	N/A. Measure is set to 0 if child does not have mental health services.	Rate
Substance abuse services per year	Number of SAMH substance abuse treatment episodes occurring over duration of SA service receipt within study window. Measure includes left-censored services[b]	N/A. Measure is set to 0 if child does not have substance abuse services.	Rate
Medicaid			
Medicaid inpatient per year	Total number of inpatient services that occurred during out-of-home placements within qualifying episodes over total duration in out-of-home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any inpatient services.	Rate
Medicaid inpatient behavioral health per year[b]	Total number of behavioral health inpatient services that occurred during out-of-home placements within qualifying episodes over total duration in out-of-home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any inpatient behavioral health services.	Rate
Medicaid inpatient physical health per year[b]	Total number of physical health inpatient services that occurred during out-of-home placements within qualifying episodes over total duration in out-of-home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any inpatient physical health services.	Rate
Medicaid outpatient per year	Total number of outpatient services that occurred during out-of-home placements within qualifying episodes over total duration in out-of-home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any outpatient services.	Rate
Medicaid outpatient behavioral health per year[b]	Total number of behavioral health outpatient services that occurred during out-of-home placements within qualifying episodes over total duration in out-of-home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any outpatient behavioral health services.	Rate

Measure	Definition	Treatment of missing values	Measurement specification
Medicaid outpatient physical health per year[b]	Total number of physical health outpatient services that occurred during out-of-home placements within qualifying episodes over total duration in out of home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any outpatient physical health services.	Rate
Medicaid emergency per year	Total number of services received in emergency departments that occurred during out-of-home placements within qualifying episodes over total duration in out of home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any emergency services.	Rate
Medicaid emergency behavioral health per year[b]	Total number of behavioral health emergency services that occurred during out-of-home placements within qualifying episodes over total duration in out of home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any emergency behavioral health services.	Rate
Medicaid emergency physical health per year[b]	Total number of physical health emergency services that occurred during out-of-home placements within qualifying episodes over total duration in out of home placements during qualifying episodes[d]	N/A. Measure is set to 0 if child does not have any emergency health services.	Rate

Note: "N/A" indicates that there were no missing values for the specific measure.

[a]Contact duration is defined by the number of days between (1) the start date of first service within the study window and (2) the latest date among the (a) e last qualifying custody episode, (b) last in-home only episode starting in the study window, or (c) date of the last Eckerd service that started in the study window. After calculating services per day of contact duration, services per year was calculated by converting the rate in days to years by multiplying by 365. For example, *Eckerd services per year* = count of Eckerd services/contact duration*365. When a duration was less than 7 days, we recoded these cases to have a duration of 7 days. This was done in order to include the information in our sample while also down-weighting the probability that a very short duration would make the case likely to be flagged for superutilization. The alternative would be to discard these cases altogether; however, we decided to err on the side of inclusiveness in our analysis. If services or episodes were right-censored, we considered them to end on the last day of the study window for the purposes of calculating contact duration. Eckerd services had a single payment date so prorating cost is not relevant to this measure.

[b]Measure was omitted in analysis.

[c]Contact duration is defined by the number of days between (1) the start date of first service within the study window, or the start of the study period if the case is left-censored, and (2) the last discharge date or end of study window if case is right-censored. After calculating services per day of contact duration, services per year was calculated by converting the rate in days to years by multiplying by 365. For example, *substance abuse services per year* = count of substance abuse services/contact duration*365. When a duration was less than 7 days, we recoded these cases to have a duration of 7 days. This was done in order to include the information in our sample while also down-weighting the probability that a very short duration would make the case likely to be flagged for superutilization. The alternative would be to discard these cases altogether; however, we decided to err on the side of inclusiveness in our analysis.

[d]A qualifying episode is an episode in which the first out-of-home placement starts in the study window. If the episode was right-censored, we included it but considered it to end on the last day of the study window.

This page has been left blank for double-sided copying.

APPENDIX C

CHARACTERISTICS AND SERVICES OF THE SUPERUTILIZATION SAMPLE

This page has been left blank for double-sided copying.

TABLES

Tables presented in Appendix C compare characteristics among the portion of the sample within each study site who were identified as children experiencing superutilization of services, referred to as the superutilization sample (SU), with the characteristics of those who were not, referred to as non-superutilization samples (nonSU). Section A depicts the results for Tennessee and Section B depicts the results for Hillsborough, Pinellas, and Pasco counties in Florida. A summary of key findings is discussed in Chapter VI.

A. Tennessee

1. Characteristics of those experiencing superutilization

C.1. Tennessee: Age among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU-% nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Less than 1	2,181	17.7	1,302	13.9	3.7**
1 to less than 6 years old	2,830	22.9	3,254	34.8	-11.9**
6 to less than 13 years old	3,111	25.2	2,854	30.6	-5.3**
13 to less than 18 years old	4,198	34.0	1,914	20.5	13.5**
18 to less than 24 years old	3	0.0	3	0.0	0.0
Missing	9	0.1	13	0.1	-0.1
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: Age was calculated at time of first custodial episode that started within the study window. Age information was set to missing for all children with reported ages of 24 and older. This cutoff is consistent with extended foster-care age restrictions in Tennessee.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.2. Tennessee: Demographics among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU-% nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Gender					
Male	6,360	51.6	4,630	49.6	2.0**
Female	5,965	48.4	4,708	50.4	-2.0**
Unknown	7	0.1	2	0.0	0.0
Race/ethnicity					
White	9,334	75.7	7,100	76.0	-0.3
Black/African American	3,240	26.3	2,183	23.4	2.9**
Hispanic/Latino	591	4.8	475	5.1	-0.3
Asian	29	0.2	22	0.2	0.0
American Indian/Alaska Native	53	0.4	23	0.2	0.2*
Native Hawaiian/other Pacific Islander	27	0.2	12	0.1	0.1
Multiracial when one race is unknown[a]	70	0.6	63	0.7	-0.1
Missing	278	2.3	415	4.4	-2.2
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: Race and ethnicity values are not mutually exclusive.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]"Multiracial when one race is unknown" is a SACWIS race value that is selected for persons suspected or known to be more than one race, but for whom only one race has been identified.

C.3. Tennessee: Superutilization and non-superutilization samples by child welfare region

	Superutilization		Non-superutilization		Difference (% SU-% nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
DCS regions					
Davidson	597	4.8	462	4.9	-0.1
East Tennessee	843	6.8	557	6.0	0.9**
Knox	1,002	8.1	714	7.6	0.5
Mid-Cumberland	979	7.9	991	10.6	-2.7**
Northeast	886	7.2	659	7.1	0.1
Northwest	484	3.9	410	4.4	-0.5
Shelby	1,150	9.3	847	9.1	0.3
Smoky Mountain	1,041	8.4	839	9.0	-0.5
South Central	574	4.7	481	5.1	-0.5
Southwest	435	3.5	374	4.0	-0.5
Tennessee Valley	894	7.2	701	7.5	-0.3
Upper Cumberland	889	7.2	991	10.6	-3.4**
Child Abuse Hotline	2	0.0	2	0.0	0.0
DCS Central Office	4	0.0	2	0.0	0.0
SIU	1,570	12.7	565	6.0	6.7**
Missing	982	8.0	745	8.0	0.0
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: Children were allocated to region based on the region associated with the last-closed investigation. A map of Tennessee DCS regions can be found via the following link: https://www.tn.gov/assets/entities/dcs/attachments/DCS_Regional_Map_June_2016.pdf.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.4. Tennessee: Reason for removal among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Reasons for removal:					
Neglect (alleged/reported)	4,655	37.7	3,550	38.0	-0.3
Drug abuse (parent)	4,366	35.4	3,957	42.4	-7.0**
Child's behavioral problem[a]	2,323	18.8	579	6.2	12.6**
Abandonment	1,539	12.5	821	8.8	3.7**
Physical abuse (alleged/reported)	1,467	11.9	974	10.4	1.5**
Incarceration of parent(s)	1,077	8.7	1,035	11.1	-2.3**
Caretaker inability to cope due to illness or other reasons	1,202	9.7	686	7.3	2.4**
Inadequate housing	1,032	8.4	923	9.9	-1.5**
Drug abuse (child)	365	3.0	124	1.3	1.6**
Sexual abuse (alleged/reported)	683	5.5	458	4.9	0.6*
Truancy	556	4.5	318	3.4	1.1**
Alcohol abuse (parent)	321	2.6	268	2.9	-0.3
Relinquishment	215	1.7	101	1.1	0.7**
Death of parent(s)	115	0.9	115	1.2	-0.3*
Alcohol Abuse (child)	45	0.4	18	0.2	0.2*
Child's disability	103	0.8	8	0.1	0.7**
Neonatal abstinence syndrome (NAS) Prosecution	1	0.0	1	0.0	0.0
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: The share reported for each reason for removal is the share of children who were placed in at least one custody episode for that reason. The case manager is able to check multiple reasons for removal.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]"Child's behavioral problem" is not an allegation type, and refers to situations where the child comes into custody through the court, and has behavioral issues that the parents cannot address and/or control (e.g., aggressive behaviors, chronic runaway behaviors, oppositional/defiance towards parents and authority figures). Case managers are able to check multiple reasons for removal, so they may check this box in addition to the allegation that resulted in the child's removal, if significant behavioral problems exist for the child/youth and the parents are unable to respond appropriately.

C.5. Tennessee: CANS and FAST assessments among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		
	Number of children	Percentage of children	Number of children	Percentage of children	Difference (% SU-% nonSU)
CANS	8,329	67.5	5,469	58.6	
Level 1	5,855	70.3	5,032	92.0	-21.7**
Level 2	1,861	22.3	370	6.8	15.6**
Level 3	515	6.2	65	1.2	5.0**
Level 4	98	1.2	2	0.0	1.1**
FAST	6,172	50.0	4,626	49.5	
Low	4,305	69.8	3,303	71.4	-1.7
Moderate	1,369	22.2	939	20.3	1.9*
High	498	8.1	384	8.3	-0.2

Source: Tennessee DCS; TennCare.

Note: Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.6. Tennessee: Life Skills and YLS assessments among superutilization and non-superutilization samples

	Superutilization				Non-superutilization				Difference (mean SU-mean nonSU)
	Number of children	Percentage of children	Mean	Std Dev	Number of children	Percentage of children	Mean	Std Dev	
Ansell-Casey Life Skills	3,092	25.1	33.9	32.7	1,535	16.4	40.2	34.5	-6.3**
YLS	286	2.3	12.6	6.1	105	1.1	11.0	5.8	1.6*

Source: Tennessee DCS; TennCare.

Note: The n value is the number of children with any assessment. The scoring range for the Ansell-Casey Life Skills assessment is 0–100. The scoring range for the YLS assessment is 0–40.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

2. Definitional characteristics of service use among those experiencing superutilization

C.7. Tennessee: Permanency among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Exited custody	8,093	65.6	7,113	76.2	-10.5 **
Remained in custody	4,239	34.4	2,227	23.8	10.5 **
Permanency outcome among children who exited custody:					
Reunification	3,786	46.8	3,446	48.4	-1.7*
Relative/kinship placement	1,493	18.4	1,569	22.1	-3.6**
Adoption	1,488	18.4	1,124	15.8	2.6**
Emancipation	920	11.4	332	4.7	6.7**
Guardianship	323	4.0	589	8.3	-4.3**
Death	34	0.4	2	0.0	0.4**
Other	49	0.6	51	0.7	-0.1
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit. Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.8. Tennessee: Child welfare history among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Prior child welfare history					
Prior investigations	5,977	48.5	3,713	39.8	8.7**
Prior child welfare custodial episode	2,129	17.3	14	0.1	17.1**

Source: Tennessee DCS; TennCare.

Note: Prior episodes and prior investigations include episodes or investigations that started prior to the study window. The count of prior investigations excludes any investigations that are associated with an episode that began during the study window. The number of episodes and placements includes ones that are right-censored, meaning they are ongoing at the end of the study time period.

In Tennessee, an episode is defined as a period of time in out-of-home care, but may also include trial home visits before child welfare custody ends.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.9. Tennessee: Number of foster care episodes over life of child among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
One episode	9,115	73.9	9,321	99.8	-25.9**
Two episodes	2,678	21.7	19	0.2	21.5**
Three episodes	428	3.5	0	0.0	3.5**
Four or more episodes	111	0.9	0	0.0	0.9**
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: In Tennessee, an episode is defined as a period of time in out-of-home care, but may also include trial home visits before child welfare custody ends.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.10. Tennessee: Average number of foster care placement moves per child, across all episodes among superutilization and non-superutilization samples

	Superutilization	Non-superutilization	Difference (SU-NonSU)
Mean	4.3	2.2	2.2**
Median	3.0	2.0	–
Min	1.0	1.0	–
Max	42.0	10.0	–

Source: Tennessee DCS; TennCare.

Note: Statistics other than the mean were not tested for significance, so the absence of significance flags does not indicate the absence of significant differences.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.11. Tennessee: Share of time spent in family foster care, or group, institutional care among superutilization and non-superutilization samples

	Superutilization				Non-superutilization				Difference (mean SU-mean nonSU)
	Mean (%)	Med (%)	Min (%)	Max (%)	Mean (%)	Med (%)	Min (%)	Max (%)	
Average share of time spent in custody by placement type:									
Family foster care	73.8	90.1	0.0	100.0	85.1	100.0	0.0	100.0	-11.3**
Group or congregate care	13.6	0.0	0.0	100.0	0.8	0.0	0.0	93.3	12.7**
Number of children	**12,332**				**9,340**				

Source: Tennessee DCS; TennCare.

Note: The average share of time spent in custody by placement type is calculated as the ratio of days spent in a specific placement type over total days spent in custody for each child. Placements with missing start or end dates or missing placement type are excluded from the analysis. As a result, these estimates may underestimate time in each placement type.

Family foster care includes the following placement types: foster family home (non-relative), foster family home (relative), pre-adoptive home, and relative. Group or congregate care includes the following placement types: group home, institution, and residential treatment. The distribution is calculated across all children in custody, including children who were not in foster care/group care.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.12. Tennessee: Children receiving child welfare services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU-% nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Children receiving child welfare services	10,926	88.6	7,294	78.1	10.5**
Among children receiving child welfare services:					
Children receiving custodial services	10,432	95.5	6,864	94.1	1.4**
Children receiving noncustodial services	3,277	30.0	1,992	27.3	2.7**
Total number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.13. Tennessee: Average number of child welfare services for those receiving services among superutilization and non-superutilization samples

	Superutilization					Non-superutilization					Difference (mean SU- mean nonSU)
	N	Mean	Med	Min	Max	N	Mean	Med	Min	Max	
Average number of services received per child	10,926	7	5	1	88	7,294	4	3	1	43	3**
Among children receiving child welfare services:											
Average number of custodial services received per child	10,432	6	4	1	88	6,864	4	3	1	28	3**
Average number of noncustodial services received per child	3,277	3	2	1	34	1,992	3	2	1	30	0**

Source: Tennessee DCS; TennCare.

Note: Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Distributions calculated across those receiving services.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.14. Tennessee: Number and type of child welfare services for those receiving services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		
	Number of children	Percentage of children	Number of children	Percentage of children	Difference (% SU- % nonSU)
Types of services received among children receiving child welfare services:					
Clothing assistance	7,660	70.1	5,425	74.4	-4.3**
Substance abuse testing and treatment[a]	3,306	30.3	2,031	27.8	2.4**
Family/parenting support	2,562	23.4	1,086	14.9	8.6**
Assessment	2,544	23.3	1,133	15.5	7.8**
Transit assistance	2,193	20.1	851	11.7	8.4**
Therapy/counseling	2,120	19.4	1,269	17.4	2.0**
Supervised visitation	2,086	19.1	786	10.8	8.3**
Legal	2,085	19.1	1,285	17.6	1.5*
Documentation	1,755	16.1	1,137	15.6	0.5
Caregiver/parenting	947	8.7	357	4.9	3.8**
Housing assistance	936	8.6	477	6.5	2.0**
Child care assistance	795	7.3	341	4.7	2.6**
Education support	433	4.0	175	2.4	1.6**
Respite	322	2.9	164	2.2	0.7**
Extension of foster care	217	2.0	70	1.0	1.0**
Language/interpretation	193	1.8	95	1.3	0.5*
Independent living support	173	1.6	69	0.9	0.6**
Youth enrichment/support	130	1.2	66	0.9	0.3
Drivers education support	68	0.6	20	0.3	0.3**
Employment/training	53	0.5	18	0.2	0.2*
Mentoring	41	0.4	13	0.2	0.2*
Health	27	0.2	17	0.2	0.0
Burial assistance	24	0.2	1	0.0	0.2**
Other[b]	3,584	32.8	1,498	20.5	12.3**
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]Substance abuse services consist primarily of testing services.

[b]Other services include other support services, paternity testing, surveillance/monitoring, and temporary breaks.

C.15. Tennessee: Medicaid services for those receiving services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU-% nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Medicaid services	10,882	88.2	7,672	82.1	6.1**
Inpatient services	2,907	23.6	771	8.3	15.3**
Physical health	1,808	62.2	675	87.5	-25.4**
Behavioral health	1,326	45.6	124	16.1	29.5**
Outpatient services	10,861	88.1	7,643	81.8	6.2**
Physical health	10,829	99.7	7,613	99.6	0.1
Behavioral health	7,735	71.2	4,132	54.1	17.2**
Emergency services	9,172	74.4	6,014	64.4	10.0**
Physical health	9,103	99.2	5,991	99.6	-0.4**
Behavioral health	1,367	14.9	229	3.8	11.1**
Number of children	**12,332**		**9,340**		

Source: Tennessee DCS; TennCare.

Note: Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.16. Tennessee: Number and type of Medicaid services for those receiving services among superutilization and non-superutilization samples

	Superutilization				Non-Superutilization				Difference (Mean SU-Mean NonSU)
	Mean	Med	Min	Max	Mean	Med	Min	Max	
Average number of inpatient services per child	2.0	1.0	1.0	29.0	1.3	1.0	1.0	23.0	0.6**
Physical health	1.6	1.0	1.0	27.0	1.3	1.0	1.0	17.0	0.3**
Behavioral health	2.2	1.0	1.0	22.0	1.4	1.0	1.0	6.0	0.7**
Average number of outpatient services per child	45.7	31.0	1.0	454.0	24.9	18.0	1.0	420.0	20.8**
Physical health	17.5	14.0	1.0	177.0	14.8	12.0	1.0	102.0	2.7**
Behavioral health	39.7	25.0	1.0	408.0	18.8	11.0	1.0	405.0	20.9**
Average number of emergency services per child	5.4	4.0	1.0	103.0	3.9	3.0	1.0	40.0	1.5**
Physical health	5.1	4.0	1.0	96.0	3.8	3.0	1.0	40.0	1.3**
Behavioral health	1.7	1.0	1.0	21.0	1.3	1.0	1.0	10.0	0.4**
Number of children	**12,332**				**9,340**				

Source: Tennessee DCS; TennCare.

Note: Distributions are calculated among children receiving services.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

B. Hillsborough, Pinellas, and Pasco counties, Florida

1. Characteristics of those experiencing superutilization

C.17. Florida: Age at time of first custody/service in lifetime among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Less than 1	696	18.7	607	20.4	-1.8
1 to less than 6 years old	1,103	29.6	1,230	41.4	-11.8**
6 to less than 13 years old	1,125	30.2	807	27.2	3.0**
13 to less than 18 years old	752	20.2	286	9.6	10.5**
18 to less than 23 years old	0	0.0	0	0.0	0.0
Missing	50	1.3	39	1.3	0.0
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Age was calculated at first child welfare out-of-home placement within episodes that started in the study window. Age information was set to missing for all children with reported ages of 23 and older. This cutoff is consistent with extended foster-care age restrictions in Florida.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.18. Florida: Demographics among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Gender					
Male	1,990	53.4	1,428	48.1	5.3**
Female	1,736	46.6	1,541	51.9	-5.3**
Unknown	0	0.0	0	0.0	0.0
Race/ethnicity					
White	2,580	69.2	2,045	68.9	0.4
Black/African American	1,374	36.9	1,094	36.8	0.0
Hispanic/Latino	522	14.0	401	13.5	0.5
Asian	19	0.5	19	0.6	-0.1
American Indian/Alaska Native	12	0.3	6	0.2	0.1
Native Hawaiian/other Pacific Islander	1	0.0	1	0.0	0.0
Missing	22	0.6	11	0.4	0.2
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Race and ethnicity values are not mutually exclusive.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.19. Florida: County distribution among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		
	Number of children	Percentage of children	Number of children	Percentage of children	Difference (% SU-% nonSU)
Counties					
Hillsborough	1,885	50.6	1,566	52.7	-2.2
Pasco	752	20.2	606	20.4	-0.2
Pinellas	1,089	29.2	797	26.8	2.4*
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Children were allocated to county based on the county associated with the last-closed investigation.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.20. Florida: Assessments among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		
	Number of children	Percentage of children	Number of children	Percentage of children	Difference (% SU-% nonSU)
OCW investigation risk level	1,629	43.7	1,528	51.5	
Low (1 to <2)	40	2.5	20	1.3	1.1*
Moderate (2 to <3)	406	24.9	437	28.6	-3.7*
High (3 to <4)	889	54.6	816	53.4	1.2
Very high (4)	294	18.0	255	16.7	1.4
FARS overall score	12	0.3	3	0.1	
Low (1 to <2)	9	75.0	2	66.7	8.3
Medium (2 to <3)	3	25.0	1	33.3	-8.3
High (3)	0	0.0	0	0.0	0.0 .
FARS security domains score	12	0.3	1	0.0	
Low (1 to <2)	11	91.7	1	100.0	-8.3
Medium (2 to <3)	1	8.3	0	0.0	8.3
High (3)	0	0.0	0	0.0	0.0 .
CFARS overall score	777	20.9	156	5.3	
Low (1 to <2)	629	81.0	136	87.2	-6.2
Medium (2 to <3)	148	19.0	20	12.8	6.2
High (3)	0	0.0	0	0.0	0.0
CFARS security domains score	777	20.9	156	5.3	
Low (1 to <2)	691	88.9	146	93.6	-4.7
Medium (2 to <3)	83	10.7	10	6.4	4.3
High (3)	3	0.4	0	0.0	0.4
ASAM recommended level of care[a]	141	3.8	11	0.4	
Intervention (1 to <2)	49	34.8	4	36.4	-1.6
Methadone/medication maintenance (2 to <3)	10	7.1	2	18.2	-11.1
Outpatient detox (3 to <4)	8	5.7	1	9.1	-3.4

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Regular outpatient treatment (4 to <5)	37	26.2	2	18.2	8.1
Intensive outpatient/day treatment (5 to <6)	10	7.1	0	0.0	7.1
Residential detox (6 to <7)	22	15.6	1	9.1	6.5
Residential (7)	5	3.5	1	9.1	-5.5
ASAM placement level of care[a]	141	3.8	11	0.4	
Intervention (1 to <2)	46	32.6	3	27.3	5.4
Methadone/medication maintenance (2 to <3)	8	5.7	2	18.2	-12.5
Outpatient detox (3 to <4)	7	5.0	1	9.1	-4.1
Regular outpatient treatment (4 to <5)	44	31.2	3	27.3	3.9
Intensive outpatient/day treatment (5 to <6)	9	6.4	0	0.0	6.4
Residential detox (6 to <7)	22	15.6	1	9.1	6.5
Residential (7)	5	3.5	1	9.1	-5.5

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: The n value is the number of children with any nonmissing assessment scores. For children in Florida who had more than one assessment record, the average score for the child was used for estimates.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]ASAM score corresponds to category of recommended or actual care, ordered by intensity of care. Average score was used to allocate children to categories. Consequently, the average should be interpreted with caution, since an average score of 4 to <5 (regular outpatient treatment) may not contain any regular outpatient placements (for example, it could contain an equal number of outpatient detox and residential detox placements).

C.21. Florida: Child welfare history among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Prior child welfare history					
Prior investigations	2,109	56.6	1,393	46.9	9.7**
Prior child welfare custodial episode	770	20.7	174	5.9	14.8**

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Prior episodes and prior investigations include episodes or investigations that started prior to the study window. The count of prior investigations excludes any investigations that are associated with an episode that began during the study window. The number of episodes and placements includes ones that are right-censored, meaning they are ongoing at the end of the study time period.

In Florida, an episode is defined by any period of time in in-home or out-of-home care. Florida estimates reported in the include episodes composed entirely of in-home placements.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

2. Definitional characteristics of service use among those experiencing superutilization

C.22. Florida: Child welfare permanency among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Exited custody	1,730	46.4	1,440	48.5	-2.1
Remained in custody	1,971	52.9	1,501	50.6	2.3
Missing	25	0.7	28	0.9	-0.3
Permanency outcome among children who exited custody					
Reunification	1,090	63.0	1,077	74.8	-11.8**
Guardianship	297	17.2	227	15.8	1.4
Adoption	236	13.6	86	6.0	7.7**
Aged out or emancipated	82	4.7	24	1.7	3.1**
Death	3	0.2	0	0.0	0.2
Other	22	1.3	26	1.8	-0.5
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit. Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.23. Florida: Number of child welfare episodes over lifetime among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
One episode	2,428	65.2	2,603	87.7	-22.5**
Two episodes	929	24.9	332	11.2	13.8**
Three episodes	275	7.4	30	1.0	6.4**
Four or more episodes	94	2.5	4	0.1	2.4**
Number of children	**3,726**		**2,969**		

Source: Florida OCW data; AHCA data; Eckerd data; SAMH data.

Note: In Florida, an episode is defined by any period of time in in-home or out-of-home care. Florida estimates reported in the include episodes composed entirely of in-home placements.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.24. Florida: Number of foster care placements across all episodes among superutilization and non-superutilization samples

	Superutilization	Non-superutilization	Difference (SU-nonSU)
Mean	5.6	2.4	3.2**
Median	4.0	2.0	–
Min	1.0	1.0	–
Max	115.0	23.0	–

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Statistics other than the mean were not tested for significance, so the absence of significance flags does not indicate the absence of significant differences.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.25. Florida: Share of time spent in family foster care or residential care among superutilization and non-superutilization samples

	Superutilization				Non-superutilization				Difference (% SU-% nonSU)
	Mean (%)	Med (%)	Min (%)	Max (%)	Mean (%)	Med (%)	Min (%)	Max (%)	
Average share of time spent in custody by placement type:									
Family foster care	64.4	69.8	0.0	100.0	74.2	92.9	0.0	100.0	-9.7**
Group home or residential treatment	9.9	0.0	0.0	100.0	0.6	0.0	0.0	87.8	9.2**
Number of children	**3,726**				**2,969**				

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: The average share of time spent in custody by placement type is calculated as the ratio of days spent in a specific placement type over total days spent in custody for each child. Placements with missing start or end dates or missing placement type are excluded from the analysis. As a result, these estimates may underestimate time in each placement type.

Family foster care includes the following placement types: foster family home (non-relative), foster family home (relative), pre-adoptive home, and relative. Group or residential care includes the following placement types: group home, institution, and residential treatment. The distribution is calculated across all children in custody, including children who were not in foster care/group care.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.26. Florida: Child welfare Community Based Care (CBC) purchased services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Children receiving child welfare CBC-purchased services	1,129	30.3	196	6.6	23.7**
Among children receiving child welfare CBC-purchased services:					
Children receiving custodial services	1,011	89.5	172	87.8	1.8
Children receiving noncustodial services	197	17.4	27	13.8	3.7
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Child welfare services for Florida are CBC-purchased services provided by Eckerd. Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.27. Florida: Average number of child welfare CBC-purchased services for those receiving services among superutilization and non-superutilization samples

	Superutilization					Non-superutilization					Difference (mean SU- mean nonSU)
	N	Mean	Med	Min	Max	N	Mean	Med	Min	Max	
Average number of child welfare CBC-purchased services received per child	1,129	2.1	1.0	1.0	27.0	196	1.2	1.0	1.0	3.0	0.9**
Among children receiving child welfare CBC-purchased services:											
Average number of CBC-purchased custodial services received per child	1,011	2.0	1.0	1.0	27.0	172	1.2	1.0	1.0	3.0	0.8**
Average number of CBC-purchased noncustodial services received per child	197	1.9	1.0	1.0	20.0	27	1.3	1.0	1.0	3.0	0.7**

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Child welfare services for Florida are CBC-purchased services provided by Eckerd. Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Distributions calculated across those receiving services.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.28. Florida: Number and type of child welfare CBC-purchased services for those receiving services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Types of services received among children receiving child welfare CBC-purchased services					
Assessments	253	22.4	24	12.2	10.2**
Documentation services	191	16.9	38	19.4	-2.5
Putative father registry	170	15.1	30	15.3	-0.2
Family/caregiver support services	150	13.3	34	17.3	-4.1
Therapy/counseling	149	13.2	19	9.7	3.5
Child care assistance	88	7.8	13	6.6	1.2
Housing assistance	86	7.6	6	3.1	4.6*
Transportation assistance	76	6.7	3	1.5	5.2**
Health services	65	5.8	7	3.6	2.2
Youth support services	46	4.1	3	1.5	2.5
Education supports	42	3.7	6	3.1	0.7
Caregiver/parenting education	30	2.7	5	2.6	0.1
Substance abuse testing/treatment	29	2.6	1	0.5	2.1
Supervised visitation	12	1.1	0	0.0	1.1
Mentoring	3	0.3	0	0.0	0.3
Case management	2	0.2	0	0.0	0.2
Language/interpretation services	2	0.2	0	0.0	0.2
Respite	1	0.1	0	0.0	0.1
Legal services	0	0.0	0	0.0	0.0
Other[a]	223	19.8	38	19.4	0.4
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Child welfare services for Florida are CBC-purchased services provided by Eckerd. Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]Other services include autism spectrum, behavioral assistance, Community Kids, IV-E waiver stipend, nonspecific to any area, other, paternity testing, reimbursement, Restorative Justice Program, shipping of luggage, state institutional claim, and uninsured children.

C.29. Florida: Medicaid services for those receiving services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Medicaid services	3,513	94.3	2,613	88.0	6.3**
Inpatient services	837	22.5	300	10.1	12.4**
Physical health	577	68.9	276	92.0	-23.1**
Behavioral health	313	37.4	28	9.3	28.1**
Outpatient services	3,496	93.8	2,586	87.1	6.7**
Physical health	3,447	98.6	2,540	98.2	0.4
Behavioral health	2,256	64.5	1,099	42.5	22.0**
Emergency services	2,641	70.9	1,675	56.4	14.5**
Physical health	2,632	99.7	1,674	99.9	-0.3
Behavioral health	181	6.9	18	1.1	5.8**
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Note: Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.30. Florida: Number and type of Medicaid services for those receiving services among superutilization and non-superutilization samples

	Superutilization				Non-superutilization				Difference (mean SU- mean nonSU)
	Mean	Med	Min	Max	Mean	Med	Min	Max	
Average number of inpatient services per child	3.2	1.0	1.0	78.0	1.9	1.0	1.0	20.0	1.3**
Physical health	1.9	1.0	1.0	27.0	1.7	1.0	1.0	20.0	0.2
Behavioral health	5.0	2.0	1.0	78.0	3.5	1.0	1.0	20.0	1.5
Average number of outpatient services per child	31.6	21.0	1.0	688.0	15.7	12.0	1.0	393.0	15.9**
Physical health	12.2	9.0	1.0	131.0	10.6	8.0	1.0	70.0	1.6**
Behavioral health	30.4	18.0	1.0	658.0	12.3	7.0	1.0	390.0	18.0**
Average number of emergency services per child	3.7	3.0	1.0	70.0	2.9	2.0	1.0	34.0	0.9**
Physical health	3.6	3.0	1.0	61.0	2.9	2.0	1.0	34.0	0.8**
Behavioral health	1.7	1.0	1.0	9.0	1.3	1.0	1.0	4.0	0.4
Number of children	**3,726**				**2,969**				

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH..

Note: Distributions calculated across those receiving services.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

C.31. Florida: Substance abuse and mental health services for those receiving services among superutilization and non-superutilization samples

	Superutilization		Non-superutilization		Difference (% SU- % nonSU)
	Number of children	Percentage of children	Number of children	Percentage of children	
Any SAMH service per child	953	25.6	106	3.6	22.0**
Substance abuse services[a]	313	8.4	17	0.6	7.8**
24-hour services	16	5.1	1	5.9	-0.8
Acute services	52	16.6	0	0.0	16.6
Outpatient services	297	94.9	17	100.0	-5.1
Mental health services[a]	841	22.6	98	3.3	19.3**
24-hour services	17	2.0	1	1.0	1.0
Acute services	168	20.0	9	9.2	10.8**
Outpatient services	802	95.4	94	95.9	-0.6
Number of children	**3,726**		**2,969**		

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Notes: Distributions are calculated across those receiving services.

Services are denominated in treatment episodes. Multiple treatment episodes can occur at the same time. Counts of services by subtype of care are counts of treatment episodes that included each subtype of care.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]24-hour services include residential care levels 1–4, room & board with supervision levels 1–3, and short-term residential treatment. Acute care includes crisis stabilization, crisis support/emergency, inpatient, and substance abuse detoxification. Outpatient includes all other services, for example, assessment, intervention, outreach, prevention, methadone maintenance, FACT team, etc.

C.32. Florida: Number and type of substance abuse and mental health services for those receiving services among superutilization and non-superutilization samples

	Superutilization				Non-superutilization				Difference (Mean SU-Mean NonSU)
	Mean	Med	Min	Max	Mean	Med	Min	Max	
Any SAMH service per child	2.5	1.0	1.0	55.0	1.5	1.0	1.0	4.0	1.0**
Substance abuse services[a]	2.6	1.0	1.0	47.0	1.3	1.0	1.0	3.0	1.3**
24-hour services	1.4	1.0	1.0	3.0	1.0	1.0	1.0	1.0	0.4
Acute services	1.2	1.0	1.0	3.0	–	–	–	–	–
Outpatient services	2.6	1.0	1.0	46.0	1.2	1.0	1.0	3.0	1.4**
Mental health services[a]	1.9	1.0	1.0	17.0	1.4	1.0	1.0	4.0	0.5**
24-hour services	1.2	1.0	1.0	3.0	1.0	1.0	1.0	1.0	0.2
Acute services	2.0	1.0	1.0	10.0	1.2	1.0	1.0	3.0	0.8**
Outpatient services	1.5	1.0	1.0	7.0	1.3	1.0	1.0	4.0	0.2*
Number of children	**3,726**				**2,969**				

Source: Florida OCW; Florida AHCA; Florida Eckerd; Florida SAMH.

Notes: Distributions are calculated across those receiving services.

Services are denominated in treatment episodes. Multiple treatment episodes can occur at the same time. Counts of services by subtype of care are counts of treatment episodes that included each subtype of care.

Estimate of the difference between groups is significantly different from zero at the ** 0.01 level or * 0.05 level.

[a]24-hour services include residential care levels 1–4, room & board with supervision levels 1–3, and short-term residential treatment. Acute care includes crisis stabilization, crisis support/emergency, inpatient, and substance abuse detoxification. Outpatient includes all other services, for example, assessment, intervention, outreach, prevention, methadone maintenance, FACT team, etc.

This page has been left blank for double-sided copying.

APPENDIX D

LATENT CLASS MODEL DETAILS AND DESCRIPTIVE TABLES

This page has been left blank for double-sided copying.

TABLES

A. Latent class model selection

In this section, we elaborate on our approach to estimating and finalizing the latent class models used to identify the types of superutilization in Tennessee and Florida. We used a multistep process to estimate, examine, and select the final latent class models presented in the report. Below, we briefly outline these steps and provide additional information on the model-selection process.

For both the Tennessee and Florida samples, we began by estimating a large number of models that included between one and eight latent classes for Tennessee and between one and ten latent classes for Florida. The upper range was defined partly by the large number of manifest variables we examined. Given the sizeable variable list, we allowed for a more saturated model to help ensure we did not inadvertently undercount the plausible number of latent classes. Examining a wide range of classes to start provided a good initial indication of where the classification performance dropped off sharply, enabling us to refine the number of classes relatively quickly. However, it should be noted that the placement of an upper limit for the number of latent classes we considered was also informed by the need to keep the potential number of classes manageable from a substantive standpoint. Identifying a high number of latent classes could be overwhelming for child welfare agencies with limited resources for prioritizing and monitoring children with diverse sets of needs or utilization patterns. Accordingly, we set the upper limit on the number of latent classes to balance the potentially wide array of latent classes that may exist with the need to keep that number manageable, actionable, and policy-relevant. For Tennessee, estimating to up to 8 classes was sufficient. For Florida, we determined that an examination of up to 10 classes was needed. The total number of classes we considered is similar to other recent LCA work using large-scale administrative data for juveniles (Bright and Johnson-Reid, 2015).

Upon estimation of the initial set of latent class models, we examined each of the model results to assess comparative performance based on a number of prespecified criteria. We narrowed the list of candidate models based on joint consideration of several factors, including model fit to data, parsimony, classification accuracy, and interpretability. Specifically, we focused on the following:

- **Information criteria.** We examined the Akaike Information Criterion (AIC), sample-size-adjusted AIC (aAIC), Bayesian Information Criterion (BIC), and the sample-size adjusted BIC (aBIC). Lower values of these measures are preferable to higher values. In examining these penalized information criteria, we preferred models with lower AIC or BIC values; however, because these measures improve (decrease) with the addition of more classes, we did not necessarily prefer the models with the absolute lowest values. Instead, we preferred models that did not show appreciable improvements in model fit when additional classes were estimated. Similarly, we also examined the family of likelihood ratio test statistics that can also be used to assess model fit. These measures include the Vuong-Lo-Mendell-Rubin likelihood ratio (VLMR) test, the Lo-Mendell-Rubin adjusted likelihood ratio (LMR) test, and the parametric bootstrapped likelihood ratio (BLR) test. However, as with the AIC and

BIC, these methods can potentially lead to overfitting the number of latent classes.[15] Moreover, these measures are most useful for testing nested models and are not typically appropriate for examining non-nested models (e.g., comparing a 1-class vs. 3-class model). Thus, in our decision-making framework, we relied more heavily on the information criteria to make the final model selection determination.

- **Change in information criteria.** To help weigh minimization of information criteria with parsimony, we also examined how the value of the information criteria changed from one n-class model to another n+1-class model. Although the level of the information criteria should improve (that is, become smaller) when a higher class model is estimated, the change in the value is also informative with respect to how much improvement a more complex model actually produces. In general, small changes in the information criteria indicate diminishing returns in terms of fit compared to enhanced model complexity. Inspecting the change in values is similar to examining a scree plot in traditional factor analysis with a leveling off of the difference in values indicating diminishing returns to additional model complexity

- **Cross-classification accuracy.** How cleanly the LC models can separate sample members into distinct classes is an important component of classification accuracy. In assessing the estimation results, we preferred models that minimized misclassification across latent classes. This was assessed by examining the n x n cross-classification matrix for each latent class model that satisfied the information criteria. Specifically, we preferred models that produced diagonal elements closer to one in the classification matrix while minimizing the values of the off-diagonal elements (that is, greater misclassification error). In addition to the classification matrix, we also examined entropy, which provides a supplemental measure of the probability of misclassification. The entropy measure is scaled from 0 to 1, with higher values indicating a higher probability of correct classification within latent classes. A general rule of thumb is that entropy should be at least 0.80 or higher. In addition to the previous considerations, we only considered models that produced entropy coefficients of at least 0.80 when considering the final LC models. High entropy has also been proposed as a measure of model fit (Soromenho, 1996); however, it should be noted that low entropy does not necessarily indicate lack of fit, which is why we emphasize the measure more in the context of classification error. In conjunction with the other statistical criteria, we consider models with low cross-classification error and higher entropy to be preferable to those with higher error and lower entropy.

- **Interpretability of the latent classes.** Once all the previously mentioned statistical criteria were satisfied, we prioritized models with more easily interpreted latent classes. This involved input from subject matter experts to make the final decisions regarding the models that were most policy-relevant. When considering multiple latent class models that were plausible on the basis of the statistical criteria listed above, we prioritized interpretability in

[15] Nylund et al (2007) find, for example, that the Type I error rate (i.e., incorrectly rejecting the H0 hypothesis that a lower-class model is correct vs. the next highest-class model) is 0.73 for sample sizes of 1,000 with a 10-item structure. By contrast, the BLR test has only a slightly inflated Type I error rate of 0.06. Nevertheless, while we examined all three likelihood ratio tests, we prioritized interpretability over fit even when a higher order latent class model may have been suggested by the likelihood ratio tests.

making the final determination. Below, we provide two examples of these considerations when discussing the Tennessee and Florida results.

In conjunction with the criteria listed above, we also took steps to ensure that the results we obtained from the maximum likelihood expectation maximization algorithm used to estimate the latent class models produced global rather than local solutions. To accomplish this, we varied the number of random starts used to check that the best log likelihood value was replicated, varying them from an initial value of 100 up to 2,400 depending on the number needed to replicate the best log likelihood. Once the best log likelihood was achieved, we set the random seed manually so that all class results were fully replicable (Muthén 2010).

Finally, we note our approach to programming. We conducted LCA using the statistical software package Mplus (Muthén 2010), with data management, model comparison, and output formatting conducted in R. Mplus was necessary to calculate the full range of model diagnostics and statistics; however, it is specialized software that requires its own special data format, only allows for the computation of one model at a time, and outputs its results in an unstructured text file. To circumvent these limitations and compare candidate latent class models, we used the R package MplusAutomation (Hallquist and Wiley 2011), which provides an interface between R and Mplus. This enabled correct data formatting and running multiple input files in batch mode.

Below, we provide the summary output from our LCA. We provide analysis results separately for Tennessee and Florida.

1. Tennessee latent class results

Tables D.1 and D.2 summarize the key model fit and classification results for the full list of latent class models that we considered. As noted above, we examined a 1-class up to an 8-class model for Tennessee. The results reported in D.1 summarize the information criteria that we examined to assess model fit. D.2 summarizes the change in the information criteria comparing the higher-order class with the next one below; as discussed previously, smaller differences between models may indicate diminishing returns to model fit for greater model complexity (i.e., less parsimony). As expected, the results in D.2 indicate that the overall model fit, as judged by the various information criteria, improves (becomes smaller) with a larger number of latent classes. However, the relative improvement in the information criteria, as summarized in D.2, appears to diminish with a higher number of latent classes.

Based on model fit and classification accuracy, we narrowed the final list of models down to two candidates—namely, a 5-class and a 7-class model. From a purely statistical perspective, both models are reasonable choices. The 5-class model was appealing because, in addition to good performance on fit and entropy, it is a more parsimonious solution than the 7-class model. Ultimately, however, we preferred the 7-class model primarily on the basis of interpretation, as it was better able to differentiate across certain measures of superutilization compared to the 5-class model. Specifically, the 5-class model contained one particularly large latent class (43 percent of the sample) that was distinguished primarily by predicted probabilities ranging between 0.46 and 0.51 on three superutilization measures (total episodes length of stay, total number of episodes, and total number of placement moves).

By contrast, the 7-class model generated classes that were more sharply differentiated across these measures and were thus more directly policy-relevant. As discussed in Chapter VII, Class 1 in the 7-class model was sharply differentiated by the total number of placement moves (predicted probability = 1) while still retaining moderate predicted probabilities for the total number of episodes and total episodes length of stay (and retained consistent predicted probabilities for the other measures as well). Thus, Class 1 in the 7-class model could be seen as a more sharply distinguishable version of the more moderately discriminating class in the 5-class solution. Similarly, the 7-class model also produced Class 2, which was differentiated based on the total number of episodes (predicted probability = 1) while also having low probabilities for the total episodes length of stay and total number of placement moves. Finally, Class 4 in the 7-class solution was distinguished by superutilization on the total episodes length of stay measure (predicted probability = 1) with low probability of superutilization on the other two measures (predicted probabilities = 0). Based on subject matter expert review, we determined that the 7-class model was preferable because it clearly differentiated children across these measures in ways that would be more actionable for child welfare agencies.

D.1. Summary of Tennessee latent class models examined

Number of Classes	Model Information Criteria: AIC	Adjusted AIC[a]	BIC	Adjusted BIC[a]	Entropy	VLMR[b] test mean
1	118494.799	118494.816	118568.998	118537.22	–	–
2	111543.65	111543.725	111699.469	111632.733	0.896	11.743**
3	109242.931	109243.102	109480.370	109378.677	0.743	19.453**
4	107844.610	107844.917	108163.668	108027.019	0.743	19.628**
5	106221.456	106221.939	106622.134	106450.528	0.837	-2.112**
6	105624.751	105625.450	106107.048	105900.485	0.826	70.006**
7	104874.232	104875.187	105438.149	105196.629	0.901	-56.573**
8	104198.765	104200.015	104844.301	104567.825	0.872	16.833**

Source: Tennessee DCS; TennCare.

Note: Estimate of the difference between groups is significantly different from zero at the **0.01 level.

[a]Adjusted AIC and BIC are based on sample size adjustment using the general formula: adjusted n = (n +2 / 24).

[b]Vuong-Lo-Mendell-Rubin Likelihood Ratio Test comparing the specified class model to the next lowest model; results were the same for the Lo-Mendell-Rubin adjusted likelihood ratio (LMR) test and the parametric bootstrapped likelihood ratio (BLR) test

D.2. Tennessee summary of change in latent class model fit statistics

Class comparisons	Difference in model information criteria: AIC	Adjusted AIC	BIC	Adjusted BIC
2 vs.1	-6951.149	-6951.091	-6869.529	-6904.487
3 vs. 2	-2300.719	-2300.623	-2219.099	-2254.056
4 vs. 3	-1398.321	-1398.185	-1316.702	-1351.658
5 vs. 4	-1623.154	-1622.978	-1541.534	-1576.491
6 vs. 5	-596.705	-596.489	-515.086	-550.043
7 vs. 6	-750.519	-750.263	-668.899	-703.856
8 vs. 7	-675.467	-675.172	-593.848	-628.804

Source: Tennessee DCS; TennCare.

Note: The results are based on the difference between the information criteria generated from the next highest class model and the next lowest.

D.3. Tennessee cross-classification matrix for seven-class model

Most likely latent class membership	Latent class						
	1	2	3	4	5	6	7
1	**0.939**	0.000	0.005	0.000	0.007	0.003	0.046
2	0.000	**0.915**	0.005	0.000	0.028	0.013	0.039
3	0.004	0.003	**0.961**	0.000	0.002	0.011	0.019
4	0.000	0.000	0.004	**0.953**	0.000	0.000	0.043
5	0.000	0.000	0.018	0.000	**0.910**	0.000	0.071
6	0.032	0.000	0.010	0.000	0.000	**0.924**	0.034
7	0.027	0.010	0.021	0.012	0.017	0.000	**0.913**

Source: Tennessee DCS; TennCare.

Note: The cross-classification matrix is based on the average latent class probabilities for the most likely latent class membership. The diagonal elements of the matrix indicate most likely class assignment whereas the off-diagonal elements indicate possible misclassification.

2. Florida latent class results

Tables D.4 and D.5 summarize the key model fit and classification results for the full list of latent class models that we considered. As noted above, we examined a 1-class up to a 10-class model for Florida. Similar to the Tennessee results discussed above, the results in D.4 indicate that the overall model fit improves with a larger number of latent classes while the relative improvement in the information criteria, as summarized in D.5 appears to diminish with a higher number of classes. It should be noted, however, that the entropy does not reach the 0.80 threshold until a 7-class model is estimated; the entropy coefficient increases to 0.86 with the 8-class model and subsequently stabilizes close to this number for higher order models. The improvement in model fit appears to first level off between the 7- and 8-class models.

Based solely on statistical criteria, the 7-class and 8-class models were both appealing. Ultimately, however, we determined that the 8-class model provided a more substantive and policy-relevant set of classes. In particular, the 7-class model included one large class (35 percent of the sample) that was not as strongly differentiated on certain measures compared to the 8-class solution. For example, this large class was moderately differentiated based on the total number of episodes and the total number of placement moves (predicted probabilities = 0.52). In contrast, the 8-class model produced two classes that were sharply differentiated on these measures. As discussed in Chapter VII, Class 4 in the 8-class model was distinguishable based on a high probability of superutilization based on the total number of placement moves (predicted probability = 1). Similarly, Class 5 in the 8-class model was distinguishable based on a high probability of superutilization on the total number of episodes (predicted probability = 1). Ultimately, we determined that these classes could be more readily interpreted and were more policy-relevant, which, in addition to already possessing desirable statistical properties, led us to select the 8-class model.

D.4. Summary of Florida latent class models examined

Number of classes	Model information criteria					VLMR[b] test mean
	AIC	Adjusted AIC[a]	BIC	Adjusted BIC[a]	Entropy	
1	37215.328	37215.257	37283.711	37248.758	–	–
2	36181.32	36181.618	36324.451	36251.368	0.616	15.316**
3	35262.293	35262.975	35480.102	35368.888	0.702	17.675**
4	34916.704	34917.930	35209.189	35059.846	0.739	7.033**
5	34628.478	34630.409	34995.64	34808.166	0.762	45.119**
6	34430.100	34432.898	34871.939	34646.335	0.779	14.445**
7	34183.066	34186.894	34699.582	34435.848	0.800	19.113**
8	34008.893	34013.917	34600.087	34298.222	0.860	-4.553**
9	33749.138	33755.526	34415.009	34075.014	0.867	9.936**
10	33629.967	33637.887	34370.515	33992.39	0.872	84.441**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Estimate of the difference between groups is significantly different from zero at the **0.01 level.

[a]Adjusted AIC and BIC are based on sample size adjustment using the general formula: adjusted n = (n +2 / 24)

[b]Vuong-Lo-Mendell-Rubin Likelihood Ratio Test comparing the specified class model to the next lowest model; results were the same for the Lo-Mendell-Rubin adjusted likelihood ratio (LMR) test, and the parametric bootstrapped likelihood ratio (BLR) test

D.5. Florida summary of change in latent class model fit statistics

	Difference in model information criteria			
Class comparisons	AIC	Adjusted AIC	BIC	Adjusted BIC
2 vs.1	-1034.008	-1033.639	-959.26	-997.39
3 vs. 2	-919.027	-918.643	-844.349	-882.48
4 vs. 3	-345.589	-345.045	-270.913	-309.042
5 vs. 4	-288.226	-287.521	-213.549	-251.68
6 vs. 5	-198.378	-197.511	-123.701	-161.831
7 vs. 6	-247.034	-246.004	-172.357	-210.487
8 vs. 7	-174.173	-172.977	-99.495	-137.626
9 vs. 8	-259.755	-258.391	-185.078	-223.208
10 vs. 9	-119.171	-117.639	-44.494	-82.624

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: The results are based on the difference between the information criteria generated from the next highest class model and the next lowest.

D.6. Florida cross-classification matrix for eight-class model

Most likely latent class membership	Latent class							
	1	2	3	4	5	6	7	8
1	**0.885**	0.039	0.048	0.013	0.003	0.001	0.000	0.010
2	0.091	**0.806**	0.035	0.005	0.058	0.000	0.003	0.002
3	0.029	0.018	**0.931**	0.006	0.003	0.000	0.009	0.004
4	0.012	0.025	0.037	**0.900**	0.000	0.000	0.025	0.000
5	0.008	0.031	0.022	0.000	**0.936**	0.000	0.000	0.003
6	0.042	0.007	0.000	0.000	0.000	**0.951**	0.000	0.000
7	0.012	0.005	0.153	0.002	0.000	0.000	**0.795**	0.032
8	0.004	0.003	0.101	0.012	0.010	0.000	0.000	**0.870**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: The cross-classification matrix is based on the average latent class probabilities for the most likely latent class membership. The diagonal elements of the matrix indicate most likely class assignment, whereas the off-diagonal elements indicate possible misclassification.

B. Latent class descriptive analysis tables

In this section, we present the results from our descriptive analyses of characteristics and services of the final latent classes. We show the descriptive results separately for the seven-class Tennessee and eight-class Florida results. We conducted statistical testing for every pairwise comparison between the latent classes in both samples. However, due to the large number of related pairwise tests conducted (often referred to as multiple comparisons), the probability of obtaining a statistically significant result at the selected significance level ($p <. 05$) by pure chance alone greatly increases. To help keep the Type I error rate (that is, the probability of falsely rejecting the null hypothesis when it is true) within 5 percent, we applied the Marascuilo

(1966) procedure for comparing multiple proportions across groups.[16] Although this approach helps to guard against artificially inflating the number of statistically significant findings, the large number of tests may still result in a higher than expected number of statistically significant findings. For this reason, caution should still be exercised when interpreting statistically significant differences.

1. Tennessee

D.7. Tennessee classes: Age at time of first custody in study window

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Less than 1	17.1^{BCDEFG}	3.3^{ACDFG}	24.6^{ABDEG}	40.7^{ABCEFG}	4.0^{ACDFG}	27.5^{ABDEG}	12.8^{ABCDEF}
1 to less than 6 years old	30.9^{BEFG}	16.6^{ACDFG}	28.8^{BEFG}	28.4^{BEFG}	13.1^{ACDFG}	37.8^{ABCDEG}	5.8^{ABCDEF}
6 to less than 13 years old	27.5^{FG}	32.5^{CDFG}	25.3^{BFG}	24.7^{BF}	30.6^{FG}	14.5^{ABCDEG}	20.0^{ABCEF}
13 to less than 18 years old	24.4^{BDEG}	47.5^{ACDFG}	21.2^{BDEG}	6.1^{ABCEFG}	52.2^{ACDFG}	20.1^{BDEG}	61.3^{ABCDEF}
18 to less than 24 years old	0.0	0.1	0.0	0.0	0.0	0.0	0.0
Missing	0.1	0.1	0.1	0.1	0.0	0.1	0.0
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Age was calculated at time of first custodial episode that started within the study window. Age information was set to missing for all children with reported ages of 24 and older. This cutoff is consistent with extended foster-care age restrictions in Tennessee.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level
[B]Difference between Class 2 is statistically significant at the 0.05 level
[C]Difference between Class 3 is statistically significant at the 0.05 level
[D]Difference between Class 4 is statistically significant at the 0.05 level
[E]Difference between Class 5 is statistically significant at the 0.05 level
[F]Difference between Class 6 is statistically significant at the 0.05 level
[G]Difference between Class 7 is statistically significant at the 0.05 level

[16] Formally, the test statistic for the Marasculio procedure is $cv_{ij} = \sqrt{X^2_{1-a,k-1}} * \sqrt{\frac{p_i(1-p_i)}{n_i} + \frac{p_j(1-p_j)}{n_j}}$, where $CV_{i,j}$ is the critical value for the comparison of proportions i and j from groups i and j, respectively. The critical value is the product of the two terms in the equation. The first term is the Chi-squared value at the 0.05 level of statistical significance with k-1 degrees of freedom, which is the number of latent classes in this case. The second term is the square root of the pooled variance between group i and group j. When comparing groups, the test statistic is the difference between the proportions. If this difference exceeds the critical value then the pairwise comparison is considered statistically significant.

D.8. Tennessee classes: Demographics

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Gender							
Male	53.5[B]	47.6[AG]	49.3[G]	49.7[G]	49.1[G]	48.1[G]	58.2[BCDEF]
Female	46.5[B]	52.4[AG]	50.6[G]	50.3[G]	50.9[G]	51.9[G]	41.7[BCDEF]
Unknown	0.0	0.0	0.2	0.0	0.0	0.0	0.1
Race/ethnicity							
White	76.2	72.0[DE]	76.3	79.0[B]	78.4[B]	72.9	75.5
Black/African American	27.6[E]	30.5[CE]	24.1[B]	26.8	22.3[AB]	27.5	25.5
Hispanic/Latino	3.7[C]	4.3	6.0[AD]	3.0[C]	6.2	5.5	4.8
Asian	0.1	0.1	0.3	0.2	0.2	0.3	0.3
American Indian/Alaska Native	0.4	0.3	0.4	1.0	0.6	0.2	0.4
Native Hawaiian/other Pacific Islander	0.1	0.2	0.2	0.4	0.2	0.6	0.2
Multiracial when one race is unknown [a]	0.3	0.3	1.1[D]	0.1[C]	0.4	0.5	0.7
Missing	1.7[CD]	0.7[CEFG]	3.7[ABD]	0.0[ACEFG]	2.6[BD]	3.7[BD]	2.4[BD]
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Race and ethnicity values are not mutually exclusive.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level
[B]Difference between Class 2 is statistically significant at the 0.05 level
[C]Difference between Class 3 is statistically significant at the 0.05 level
[D]Difference between Class 4 is statistically significant at the 0.05 level
[E]Difference between Class 5 is statistically significant at the 0.05 level
[F]Difference between Class 6 is statistically significant at the 0.05 level
[G]Difference between Class 7 is statistically significant at the 0.05 level

[a]"Multiracial when one race is unknown" is a SACWIS race value that is selected for persons suspected or known to be more than one race, but for whom only one race has been identified.

D.9. Tennessee classes: By child welfare region

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
DCS regions							
Davidson	4.2	6.8[G]	5.1	4.6	5.2	4.9	4.0
East Tennessee	6.1[CD]	8.0[D]	9.9[ADFG]	3.1[ABCE]	6.7[D]	6.2[C]	5.2[C]
Knox	8.4[B]	5.0[ACF]	10.8[BEG]	7.2[F]	6.4[CF]	12.3[BDEG]	5.9[CF]
Mid-Cumberland	9.2[C]	7.8[E]	5.0[AEF]	7.6[E]	12.8[BCDG]	8.6[C]	7.4[E]
Northeast	5.5[CDG]	5.0[CDG]	9.5[ABE]	9.5[ABE]	4.9[CDG]	6.3	8.8[ABE]
Northwest	2.7[C]	3.6[C]	6.3[ABDEF]	1.7[CG]	2.7[C]	3.6[C]	4.6[D]
Shelby	6.9[BCG]	13.3[ADE]	11.4[AE]	7.8[B]	5.5[BCG]	9.3	9.9[AE]
Smoky Mountain	8.3[CF]	7.0[F]	5.4[ADFG]	10.9[C]	8.5[F]	13.4[ABCE]	9.8[C]
South Central	4.4	6.6[D]	4.2	3.2[B]	6.0	4.6	4.0
Southwest	2.3[C]	3.7	5.7[AFG]	3.6	3.4	2.9[C]	2.8[C]
Tennessee Valley	6.4[DE]	7.6	4.9[DEG]	11.0[AC]	11.2[ACF]	6.8[E]	7.6[C]
Upper Cumberland	7.8[G]	7.9[G]	8.1[G]	6.2	7.3	8.5[G]	4.6[ABCF]
Child Abuse Hotline	0.0	0.0	0.0	0.1	0.0	0.0	0.0
DCS Central Office	0.0	0.1	0.0	0.0	0.2	0.0	0.0
SIU	23.0[BCEFG]	8.5[ADG]	6.4[ADG]	18.0[BCEF]	9.1[AD]	5.8[ADG]	13.1[ABCF]
Missing	5.0[BCEG]	9.0[A]	7.3[AG]	5.4[EG]	10.1[AD]	7.0[G]	12.3[ACDF]
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Children were allocated to region based on the region associated with the last-closed investigation. A map of Tennessee DCS regions can be found via the following link: https://www.tn.gov/assets/entities/dcs/attachments/DCS_Regional_Map_June_2016.pdf

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level
[B]Difference between Class 2 is statistically significant at the 0.05 level
[C]Difference between Class 3 is statistically significant at the 0.05 level
[D]Difference between Class 4 is statistically significant at the 0.05 level
[E]Difference between Class 5 is statistically significant at the 0.05 level
[F]Difference between Class 6 is statistically significant at the 0.05 level
[G]Difference between Class 7 is statistically significant at the 0.05 level

D.10. Tennessee classes: Reason for removal

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Reason for removal:							
Neglect (alleged/reported)	42.6^{DEG}	46.2^{CDEG}	38.5^{BG}	33.2^{AB}	34.2^{ABG}	39.3^{G}	27.9^{ABCEF}
Drug abuse (parent)	39.1^{BDEG}	31.7^{ACDEFG}	42.9^{BDEG}	54.4^{ABCEFG}	24.2^{ABCDF}	41.2^{BDEG}	19.5^{ABCDF}
Child's behavioral problem [a]	17.0^{BCDEFG}	24.9^{ACDFG}	7.1^{ABDEG}	2.4^{ABCEFG}	24.6^{ACDFG}	5.8^{ABDEG}	41.1^{ABCDEF}
Abandonment	13.8^{BCDF}	19.0^{ACDEF}	8.2^{ABG}	6.6^{ABEG}	11.6^{BD}	9.4^{ABG}	15.7^{CDF}
Physical abuse (alleged/reported)	14.8^{DFG}	13.8^{G}	11.6	10.2^{A}	10.8	10.4^{A}	9.2^{AB}
Incarceration of parent(s)	10.2^{G}	11.1^{G}	8.8^{G}	10.7^{G}	7.2	10.3^{G}	4.4^{ABCDF}
Caretaker inability to cope due to illness or other reasons	11.3^{D}	11.4	8.9	7.5^{A}	8.7	8.5	9.6
Inadequate housing	10.3^{G}	8.3^{G}	9.0^{G}	10.9^{G}	7.1	9.5^{G}	4.2^{ABCDF}
Drug abuse (child)	2.5^{FG}	3.4^{F}	1.8^{EFG}	1.3^{EG}	4.6^{CDF}	0.5^{ABCEG}	5.7^{ACDF}
Sexual abuse (alleged/reported)	5.6	7.4^{F}	5.2	5.4	6.7	3.6^{B}	5.0
Truancy	3.2^{BDE}	6.8^{ACDF}	3.7^{BDE}	0.9^{ABCEFG}	9.1^{ACDFG}	3.5^{BDE}	5.2^{DE}
Alcohol abuse (parent)	2.5	2.7	3.6^{G}	2.2	2.5	3.2	1.5^{C}
Relinquishment	2.0^{B}	4.1^{ACDEFG}	1.0^{B}	0.8^{B}	0.9^{B}	1.0^{B}	1.9^{B}
Death of parent(s)	0.7	1.7	1.1	0.7	1.2	1.1	0.5
Alcohol Abuse (child)	0.2	0.3	0.3	0.0^{G}	0.8	0.5	0.7^{D}
Child's disability	0.5^{G}	0.5^{G}	0.6^{G}	0.1^{G}	0.4^{G}	0.2^{G}	2.6^{ABCDEF}
Neonatal abstinence syndrome (NAS) Prosecution	0.0	0.0	0.0	0.0	0.0	0.1	0.0
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: The share reported for each reason for removal is the share of children who were placed in at least one custody episode for that reason. The case manager is able to check multiple reasons for removal.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

$^{\mathrm{A}}$Difference between Class 1 is statistically significant at the 0.05 level

$^{\mathrm{B}}$Difference between Class 2 is statistically significant at the 0.05 level

$^{\mathrm{C}}$Difference between Class 3 is statistically significant at the 0.05 level

$^{\mathrm{D}}$Difference between Class 4 is statistically significant at the 0.05 level

$^{\mathrm{E}}$Difference between Class 5 is statistically significant at the 0.05 level

$^{\mathrm{F}}$Difference between Class 6 is statistically significant at the 0.05 level

$^{\mathrm{G}}$Difference between Class 7 is statistically significant at the 0.05 level

[a]"Child's behavioral problem" is not an allegation type, and refers to situations where the child comes into custody through the court, and has behavioral issues that the parents cannot address and/or control (e.g., aggressive behaviors, chronic runaway behaviors, oppositional/defiance towards parents and authority figures). Case managers are able to check multiple reasons for removal, so they may check this box in addition to the allegation that resulted in the child's removal, if significant behavioral problems exist for the child/youth and the parents are unable to respond appropriately.

D.11. Tennessee classes: Assessments and scores

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
CANS							
Level 1	69.8^{BCDEFG}	81.6^{ADG}	84.7^{ADEG}	97.1^{ABCEFG}	77.8^{ACDG}	81.7^{ADG}	38.2^{ABCDEF}
Level 2	25.8^{BCDEFG}	13.9^{ADG}	11.7^{ADEG}	2.9^{ABCEFG}	18.2^{ACDG}	14.4^{ADG}	41.8^{ABCDEF}
Level 3	4.1^{DG}	3.5^{DG}	3.1^{DG}	0.0^{ABCEFG}	3.4^{DG}	3.2^{DG}	16.3^{ABCDEF}
Level 4	0.2^{G}	1.0^{DG}	0.4^{G}	0.0^{BG}	0.5^{G}	0.7^{G}	3.6^{ABCDEF}
Number of children	**1,939**	**1,340**	**1,362**	**486**	**934**	**431**	**1,837**
FAST							
Low	68.2^{B}	73.8^{AG}	71.0	67.3	69.2	71.9	67.6^{B}
Moderate	23.6	20.5	21.4	22.7	19.6	21.8	23.7
High	8.2	5.7^{DE}	7.6	10.0^{B}	11.2^{BF}	6.3E	8.7
Number of children	**1,508**	**805**	**1,282**	**459**	**546**	**527**	**1,045**

Source: Tennessee DCS; TennCare.

Note: Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.12. Tennessee classes: Assessments and scores

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Ansell-Casey Life Skills							
Mean	35.7^{G}	36.6^{G}	31.1^{F}	33.4	32.6	41.6^{CG}	30.3^{ABF}
Std Dev	32.7	32.5	33.2	29.2	34.4	34.3	31.6
Number of children	**771**	**570**	**349**	**132**	**340**	**162**	**768**
YLS							
Mean	14.1	11.4	10.9	9.3	11.4	10.8	13.4
Std Dev	6.5	5.6	6.2	5.7	5.7	5.5	6.0
Number of children	**52**	**52**	**17**	**4**	**38**	**13**	**110**

Source: Tennessee DCS; TennCare.

Note: The n value is the number of children with any assessment. The scoring range for the Ansell-Casey Life Skills assessment is 0–100. The scoring range for the YLS assessment is 0–40.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.13. Tennessee classes: Child welfare history prior to study window

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Prior child welfare history							
Prior investigations	58.4^{BCDEFG}	75.0^{ACDEFG}	34.0^{ABEG}	35.7^{ABEG}	51.8^{ABCDF}	29.2^{ABEG}	47.9^{ABCDF}
Prior child welfare custodial episode	34.7^{BCDEFG}	63.3^{ACDEFG}	4.4^{ABDEF}	0.7^{ABCG}	0.1^{ABCG}	0.1^{ABCG}	3.0^{ABDEF}
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Prior episodes and prior investigations include episodes or investigations that started prior to the study window. The count of prior investigations excludes any investigations that are associated with an episode that began during the study window. The number of episodes and placements includes ones that are right-censored, meaning they are ongoing at the end of the study time period.

In Tennessee, an episode is defined as a period of time in out-of-home care, but may also include trial home visits before child welfare custody ends.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.14. Tennessee classes: Permanency

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Exited custody	62.0^{EF}	67.0^{EF}	64.9^{EF}	64.2^{EF}	75.2^{ABCDG}	74.1^{ABCDG}	61.9^{EF}
Remained in custody	38.0^{EF}	33.0^{EF}	35.1^{EF}	35.8^{EF}	24.8^{ABCDG}	25.9^{ABCDG}	38.1^{EF}
Permanency type among children who exited custody:							
Reunification	48.1^{DEF}	46.0^{DEF}	48.7^{DEF}	8.6^{ABCEFG}	58.4^{ABCDG}	55.7^{ABCDG}	47.1^{DEF}
Relative/kinship placement	12.8^{CDEF}	16.0^{CDEF}	29.0^{ABDEG}	3.4^{ABCEFG}	23.4^{ABCDG}	27.3^{ABDG}	12.6^{CDEF}
Adoption	23.8^{BCDEFG}	13.2^{ADEF}	11.0^{ADEF}	80.2^{ABCEFG}	4.6^{ABCDG}	6.1^{ABCDG}	13.9^{ADEF}
Emancipation	9.2^{BDFG}	18.0^{ACDEFG}	6.7^{BDEG}	2.2^{ABCEG}	10.4^{BCDFG}	4.5^{ABEG}	23.5^{ABCDEF}
Guardianship	5.4^{CEG}	6.1^{CEG}	2.7^{ABFG}	5.3^{G}	2.7^{ABF}	6.3^{CEG}	1.2^{ABCDF}
Death	0.3^{C}	0.0^{C}	1.5^{ABDEFG}	0.0^{C}	0.0^{C}	0.0^{C}	0.3^{C}
Other	0.5	0.8	0.5	0.2^{G}	0.5	0.1^{G}	1.4^{DF}
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit. Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.15. Tennessee classes: Average time to permanency (days)

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Exited custody	62.0[BCDEFG]	67.0[ACDEFG]	64.9[ABDFG]	64.2[ABCEFG]	75.2[ABDG]	74.1[ABCDG]	61.9[ABCDEF]
Permanency type among children who exited custody							
Reunification	447.7[BCDEFG]	239.7[ACDG]	202.9[ABDFG]	922.4[ABCEFG]	231.7[ADG]	245.8[ACDG]	304.8[ABCDEF]
Relative/kinship placement	370.7[BCDEFG]	211.8[ACDEG]	110.1[ABDFG]	774.0[ABCEFG]	119.9[ABDG]	157.9[ACDG]	275.9[ABCDEF]
Adoption	799.8[BCDEFG]	701.4[ACDF]	508.3[ABDG]	941.1[ABCEFG]	605.4[AD]	473.2[ABDG]	637.6[ACDF]
Emancipation	648.9[BCDEFG]	327.5[ADG]	267.2[ADG]	1,013.2[ABCEFG]	301.0[ADG]	377.4[AD]	421.4[ABCDE]
Guardianship	596.8[BCDEF]	457.7[AD]	442.2[AD]	895.9[ABCEFG]	407.2[AD]	452.7[AD]	518.5[D]
Death	508.6[CG]	–	134.4[A]	–	–	–	81.8[A]
Other	423.0	300.5	111.4[D]	1,187.0[CE]	33.8[D]	77.0	293.8

Source: Tennessee DCS; TennCare.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit.

Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

D.16. Tennessee classes: Number of foster care episodes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Number of child welfare episodes over the life of the child							
One episode	49.8[BCDEFG]	0.0[ACDEFG]	94.1[ABDEF]	99.3[ABCG]	99.9[ABCG]	99.7[ABCG]	94.7[ABDEF]
Two episodes	37.5[BCDEFG]	90.0[ACDEFG]	5.1[ABDEF]	0.7[ABCG]	0.1[ABCG]	0.3[ABCG]	5.0[ABDEF]
Three episodes	9.4[CDEFG]	9.1[CDEFG]	0.6[ABDEF]	0.0[ABC]	0.0[ABC]	0.0[ABC]	0.3[AB]
Four or more episodes	3.3[BCDEFG]	0.9[ADEFG]	0.1[A]	0.0[AB]	0.0[AB]	0.0[AB]	0.0[AB]
Number of child welfare episodes during the study window							
One episode	79.8[BCDEFG]	59.5[ACDEFG]	98.4[ABDEF]	100.0[ABCG]	100.0[ABCG]	99.8[ABCG]	97.5[ABDEF]
Two episodes	18.9[BCDEFG]	39.5[ACDEFG]	1.4[ABDEF]	0.0[ABCG]	0.0[ABCG]	0.2[ABCG]	2.4[ABDEF]
Three episodes	1.2[CDEFG]	1.0[DEFG]	0.2[A]	0.0[AB]	0.0[AB]	0.0[AB]	0.0[AB]
Four or more episodes	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: In Tennessee, an episode is defined as a period of time in out-of-home care, but may also include trial home visits before child welfare custody ends.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

D.17. Tennessee classes: Average number of foster care placement moves per child, across all episodes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Mean	8.2^{BCDEFG}	4.4^{ACDEFG}	2.3^{ABEG}	2.5^{ABG}	2.7^{ABCG}	2.6^{ABG}	4.1^{ABCDEF}
Median	7.0	4.0	2.0	2.0	2.0	2.0	3.0
Min	3.0	2.0	1.0	1.0	1.0	1.0	1.0
Max	42.0	12.0	17.0	9.0	10.0	25.0	31.0
Number of children	**2,841**	**1,505**	**2,654**	**906**	**1,126**	**1,069**	**2,229**

Source: Tennessee DCS; TennCare.

Note: Statistics other than the mean were not tested for significance, so the absence of significance flags does not indicate the absence of significant differences.

The n value is the number of children with nonmissing placement information.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.18. Tennessee classes: Number of foster care placement moves across all custody episodes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
One move	0.0^{CDEFG}	0.0^{CDEFG}	36.5^{ABDEFG}	24.5^{ABCG}	24.7^{ABCG}	22.3^{ABCG}	10.0^{ABCDEF}
Two moves	0.0^{BCDEFG}	11.5^{ACDEFG}	31.4^{ABFG}	33.8^{ABG}	29.2^{ABFG}	38.0^{ABCEG}	21.7^{ABCDEF}
Three moves	4.3^{BCDEFG}	23.1^{AC}	16.2^{ABDFG}	22.6^{AC}	18.5^{A}	21.5^{AC}	20.9^{AC}
Four moves	15.8^{BCDF}	23.1^{ACDEFG}	8.0^{ABEG}	11.0^{AB}	14.5^{BC}	10.8^{ABG}	15.2^{BCF}
Five moves	13.4^{BCDEF}	20.8^{ACDEFG}	3.6^{ABEG}	4.5^{ABG}	7.2^{ABCFG}	3.3^{ABEG}	11.7^{BCDEF}
Six moves	11.8^{CDEFG}	9.9^{CDEF}	2.0^{ABG}	2.3^{ABG}	3.3^{ABG}	1.7^{ABG}	7.0^{ACDEF}
Seven or more moves	54.7^{BCDEFG}	11.6^{ACDEF}	2.2^{ABG}	1.2^{ABG}	2.7^{ABG}	2.5^{ABG}	13.6^{ACDEF}
Missing	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.19. Tennessee classes: Average percentage of total time spent in custody by placement type category

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Family foster care							
Mean	76.7^{CDEG}	78.0^{CDEG}	86.0^{ABDEFG}	97.1^{ABCEFG}	70.4^{ABCDFG}	78.9^{CDEG}	42.5^{ABCDEF}
Median	84.9	87.5	100.0	100.0	91.8	100.0	30.0
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Group or congregate care							
Mean	8.8^{BCDEFG}	5.8^{ACDEFG}	3.6^{ABDEFG}	0.5^{ABCEG}	13.8^{ABCDFG}	0.8^{ABCEG}	48.1^{ABCDEF}
Median	0.0	0.0	0.0	0.0	0.0	0.0	51.1
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Max	99.6	95.5	100.0	63.9	100.0	76.3	100.0
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: The average share of time spent in custody by placement type is calculated as the ratio of days spent in a specific placement type over total days spent in custody for each child. Placements with missing start or end dates or missing placement type are excluded from the analysis. As a result, these estimates may underestimate time in each placement type.

Family foster care includes the following placement types: foster family home (non-relative), foster family home (relative), pre-adoptive home, and relative. Group or congregate care includes the following placement types: group home, institution, and residential treatment. The distribution is calculated across all children in custody, including children who were not in foster care/group care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.20. Tennessee classes: Children receiving child welfare services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Children receiving child welfare services	92.0^{BCDEFG}	85.4^{ACDE}	100.0^{ABDEFG}	96.9^{ABCEFG}	70.9^{ABCDFG}	82.2^{ACDE}	81.4^{ACDE}
Among children receiving child welfare services							
Children receiving custodial services	98.5^{BCEG}	94.6^{AD}	94.2^{AD}	98.9^{BCEFG}	91.4^{ADF}	96.5^{DEG}	93.2^{ADF}
Children receiving noncustodial services	25.4^{BCDEG}	36.9^{ADF}	33.3^{ADF}	18.8^{ABCEG}	36.1^{ADF}	23.0^{BCEG}	32.9^{ADF}
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.21. Tennessee classes: Average number of child welfare services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Average number of services received per child	7^{CDEFG}	6^{CDEFG}	11^{ABDEFG}	8^{ABCEFG}	4^{ABCD}	4^{ABCDG}	5^{ABCDF}
Among children receiving child welfare services							
Average number of custodial services received per child	6^{CDEFG}	5^{CDEFG}	10^{ABDEFG}	8^{ABCEFG}	4^{ABCDG}	3^{ABCDG}	4^{ABCDEF}
Average number of noncustodial services received per child	3^{C}	3^{C}	4^{ABDEFG}	3^{C}	3^{C}	3^{C}	3^{C}
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Distributions calculated across those receiving services.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level

D.22. Tennessee classes: Number and type of child welfare services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Children receiving child welfare services	92.0 BCDEFG	85.4 ACDE	100.0 ABDEFG	96.9 ABCEFG	70.9 ABCDFG	82.2 ACDE	81.4 ACDE
Among children receiving child welfare services:							
One service	12.6 CDEFG	15.2 CDEF	7.3 ABEFG	5.4 ABEFG	25.7 ABCDG	30.4 ABCDG	19.4 ACDEF
Two services	13.0 DEF	16.1 CDF	10.3 BEFG	7.2 ABEFG	18.5 ACD	22.5 ABCDG	15.9 CDF
Three or more services	74.3 BCDEFG	68.7 ACDEF	82.4 ABDEFG	87.5 ABCEFG	55.8 ABCDFG	47.1 ABCDEG	64.7 ACDEF
Among children receiving child welfare services							
Clothing assistance	71.4 FG	74.8 G	71.5 FG	71.1 FG	69.9 FG	78.8 ACDEG	58.4 ABCDEF
Substance abuse testing and treatment[a]	28.9 CG	26.3 CG	44.9 ABDEFG	32.7 CEFG	24.1 CDG	24.3 CDG	18.1 ABCDEF
Family/parenting support	22.8 CDF	25.7 CDFG	32.4 ABDEFG	16.9 ABC	20.1 CF	12.7 ABCEG	19.5 BCF
Assessment	21.3 CF	19.3 CF	34.5 ABDEFG	22.1 CF	18.9 CF	12.7 ABCDEG	20.0 CF
Transit assistance	20.1 CEF	16.3 CEFG	25.9 ABEF	20.5 EF	11.0 ABCDG	10.2 ABCDG	22.7 BEF
Therapy/counseling	17.9 CEG	18.3 CEG	30.9 ABDEFG	21.2 CEG	10.7 ABCDF	18.0 CEG	9.3 ABCDF
Supervised visitation	15.5 CDEFG	16.3 CEFG	37.7 ABDEFG	21.2 ACEFG	11.0 ABCDG	9.2 ABCD	6.4 ABCDE
Legal	21.5 CDEFG	17.3 DEF	14.1 ADEF	63.8 ABCEFG	6.5 ABCDG	6.6 ABCDG	14.0 ADEF
Documentation	19.0 BCDEFG	14.0 ADEF	10.8 ADEF	55.6 ABCEFG	5.6 ABCDG	5.8 ABCDG	11.4 ADEF
Caregiver/parenting	8.3 CEF	7.9 CF	14.2 ABDEFG	8.1 CF	4.6 AC	4.0 ABCD	5.9 C
Housing assistance	9.8 DF	10.2 DF	7.9	5.8 AB	9.8 F	5.5 ABEG	8.9 F
Child care assistance	7.2 BCE	2.2 ACDFG	11.3 ABDEFG	7.2 BCE	3.5 ACDFG	7.4 BCE	6.8 BCE
Education support	2.9 BEG	6.5 ACDF	3.5 BF	1.8 BEG	6.3 ADF	1.5 BCEG	5.5 ADF
Respite	4.2 FG	2.9	2.6	3.1	2.8	1.8 A	2.3 A
Extension of foster care	1.0 BCG	2.7 ADF	2.8 ADF	0.5 BCG	1.9	0.5 BCG	3.2 ADF
Language/interpretation	1.1 C	0.5 C	3.7 ABEFG	2.1	0.9 C	0.7 C	1.6 C
Independent living support	1.5	1.9	1.3	0.8 G	1.9	0.7 G	2.7 DF
Youth enrichment/support	1.4	1.6	1.0	1.0	1.0	0.5	1.4
Drivers education support	0.3 EG	0.8	0.5	0.2 E	1.8 ADF	0.1 EG	1.2 AF
Employment/training	0.5	0.5	0.5	0.3	0.1	0.2	0.8
Mentoring	0.5 D	0.6	0.2	0.0 AG	0.3	0.2	0.6 D
Health	0.3	0.4	0.3	0.1	0.0	0.3	0.2
Burial assistance	0.1 C	0.0 C	0.8 ABDEFG	0.0 C	0.0 C	0.0 C	0.0 C
Other[b]	41.8 BCDEF	30.0 AEFG	27.7 AEFG	33.0 AEFG	20.3 ABCDG	20.6 ABCDG	40.6 BCDEF
Among children receiving child welfare services							
One category of services	20.8 CDEFG	25.0 CDEFG	15.1 ABDEFG	9.5 ABCEFG	36.6 ABCD	39.2 ABCDG	30.6 ABCDF
Two categories of services	20.7 CDEFG	25.0 CD	16.4 ABEFG	14.1 ABEFG	26.4 ACD	28.8 ACD	24.9 ACD
Three or more categories of services	58.6 BCDEFG	49.9 ACDEF	68.5 ABDEFG	76.4 ABCEFG	37.0 ABCDG	32.0 ABCDG	44.5 ACDEF
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level
[B]Difference between Class 2 is statistically significant at the 0.05 level
[C]Difference between Class 3 is statistically significant at the 0.05 level
[D]Difference between Class 4 is statistically significant at the 0.05 level
[E]Difference between Class 5 is statistically significant at the 0.05 level
[F]Difference between Class 6 is statistically significant at the 0.05 level
[G]Difference between Class 7 is statistically significant at the 0.05 level

[a]Substance abuse services consist primarily of testing services.

[b]Other services include other support services, paternity testing, surveillance/monitoring, and temporary breaks.

D.23. Tennessee classes: Children receiving Medicaid services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Medicaid services	87.8^{DEF}	89.5^{CDEF}	85.2^{BDEFG}	65.2^{ABCEFG}	100.0^{ABCDG}	100.0^{ABCDG}	89.3^{CDEF}
Inpatient services	21.5^{CDG}	18.7^{DG}	17.5^{ADG}	10.3^{ABCEFG}	19.5^{DG}	19.7^{DG}	46.0^{ABCDEF}
Physical health	54.4^{CDEFG}	58.0^{CDFG}	87.1^{ABDEG}	91.4^{ABCEG}	61.4^{ACDFG}	90.5^{ABEG}	48.4^{ABCDEF}
Behavioral health	53.1^{CDFG}	50.9^{CDFG}	17.2^{ABEFG}	12.9^{ABEG}	48.6^{CDFG}	12.3^{ABCEG}	61.7^{ABCDEF}
Outpatient services	87.8^{DEF}	89.4^{CDEF}	84.9^{BDEFG}	65.2^{ABCEFG}	100.0^{ABCDG}	99.6^{ABCDG}	89.0^{CDEF}
Physical health	99.9	99.9	99.7	100.0	98.9	99.9	99.5
Behavioral health	76.0^{BCDEFG}	81.0^{ACDEF}	53.5^{ABDEFG}	62.4^{ABCEFG}	91.6^{ABCDFG}	43.1^{ABCDEG}	84.9^{ACDEF}
Emergency services	75.0^{CDEF}	75.9^{CDEF}	67.3^{ABDEFG}	48.8^{ABCEFG}	83.1^{ABCDFG}	100.0^{ABCDEG}	74.7^{CDEF}
Physical health	99.2	99.6^{G}	99.8^{G}	99.8^{G}	99.1	99.8^{G}	98.1^{BCDF}
Behavioral health	15.8^{CDFG}	12.6^{CDFG}	5.6^{ABEG}	5.4^{ABEG}	16.3^{CDFG}	7.3^{ABEG}	32.0^{ABCDEF}
Number of children	**2,841**	**1,505**	**2,655**	**906**	**1,126**	**1,069**	**2,230**

Source: Tennessee DCS; TennCare.

Note: Statistical testing of all pairwise comparisons for each variable in the was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

D.24. Tennessee classes: Number and type of Medicaid services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Average number of inpatient services per child	1.9	1.9	1.7	1.3	1.5	1.4	2.4
Physical health	1.4[G]	1.6	1.7	1.2[G]	1.3[G]	1.4[G]	1.8[ADEF]
Behavioral health	2.1	1.9	1.7	1.6	1.3	1.5	2.5
Average number of outpatient services per child	53.9[EG]	47.1[G]	27.5[G]	51.3	68.4[AG]	24.9	51.9[ABCE]
Physical health	18.4[BCD]	16.0[ADF]	16.4[ADF]	21.4[ABCEFG]	17.0[D]	18.4[BCD]	17.3[D]
Behavioral health	46.7[BCEFG]	38.4[ACDEF]	20.8[ABDEG]	47.9[BCEF]	56.3[ABCDFG]	14.9[ABDEG]	40.9[ACEF]
Average number of emergency services per child	4.8[DFG]	5.2[DFG]	5.0[DFG]	3.5[ABCEFG]	5.3[DFG]	7.0[ABCDEG]	6.1[ABCDEF]
Physical health	4.6[DFG]	5.0[DF]	4.9[DFG]	3.4[ABCEFG]	5.1[DF]	6.9[ABCDEG]	5.5[ACDF]
Behavioral health	1.6[G]	1.7	1.6	1.3	1.4[G]	1.4[G]	2.0[AEF]

Source: Tennessee DCS; TennCare.

Note: Distributions are calculated among children receiving services.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

2. Florida

D.25. Florida classes: Age at time of first custody/service in lifetime

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Less than 1	17.2^{BDEFGH}	5.5^{ADFH}	9.9^{DEFGH}	59.6^{ABCEGH}	2.3^{ACDFH}	43.8^{ABCEG}	1.8^{ACDFH}	34.9^{ABCDEG}
1 to less than 6 years old	30.4	20.9^{FH}	23.0^{FH}	28.6	30.8	37.6^{BC}	29.1	40.2^{BC}
6 to less than 13 years old	29.1^{DEFH}	34.3^{DFH}	36.4^{DEFH}	5.8^{ABCEG}	47.4^{ACDFH}	11.9^{ABCEG}	40.1^{DFH}	12.6^{ABCEG}
13 to less than 18 years old	22.8^{BDFH}	37.8^{ADEFH}	28.8^{DEFH}	6.0^{ABCEG}	16.6^{BCDFG}	6.7^{ABCEG}	28.1^{DEFH}	11.7^{ABCG}
18 to less than 23 years old	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Missing	0.6	1.5	1.8^{DF}	0.0^{CE}	3.0^{DF}	0.0^{CE}	0.9	0.6
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Age was calculated at first child welfare out-of-home placement within episodes that started in the study window. Age information was set to missing for all children with reported ages of 23 and older. This cutoff is consistent with extended foster-care age restrictions in Florida.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level
^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.26. Florida classes: Demographics

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Gender								
Male	54.1	56.2	51.1	52.5	56.0	45.2	57.8	52.9
Female	45.9	43.8	48.9	47.5	44.0	54.8	42.2	47.1
Unknown	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Race/ethnicity								
White	71.1	65.7	70.3	73.5	68.8	69.0	63.3	68.2
Black/African American	35.8	43.3	34.9	31.8	35.6	41.0	40.1	41.0
Hispanic/Latino	14.7[B]	6.0[AGH]	13.5[G]	14.2	10.8[G]	14.8	23.9[BCE]	15.3[B]
Asian	0.2	0.0	0.7	0.5	0.3	0.5	1.2	0.6
American Indian/Alaska Native	0.4	0.0	0.2	0.3	0.4	1.4	0.0	0.2
Native Hawaiian/other Pacific Islander	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0
Missing	1.0	1.0	0.6	1.3	0.4	0.0	0.3	0.2
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Race and ethnicity values are not mutually exclusive.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

D.27. Florida classes: By county

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Counties								
Hillsborough	47.8^{G}	49.3^{G}	49.2^{G}	50.7^{G}	47.0^{G}	50.0^{G}	74.3^{ABCDEFH}	46.2^{G}
Pasco	22.6^{G}	17.9	16.0^{FH}	21.8	18.1^{H}	29.0^{CG}	12.5^{AFH}	29.5^{CEG}
Pinellas	29.6^{G}	32.8^{G}	34.8^{FGH}	27.6^{G}	35.0^{FGH}	21.0^{CE}	13.1^{ABCDEH}	24.3^{CEG}
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Children were allocated to county based on the county associated with the last-closed investigation.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

D.28. Florida classes: Assessments and scores

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
FARS overall score								
Low (1 to <2)	100.0^{BCE}	50.0^{AC}	80.0^{ABE}	–	50.0^{AC}	–	–	–
Medium (2 to <3)	0.0^{BCE}	50.0^{AC}	20.0^{ABE}	–	50.0^{AC}	–	–	–
High (3)	0.0	0.0	0.0	–	0.0	–	–	–
Number of children	**3**	**2**	**5**	**0**	**2**	**0**	**0**	**0**
FARS security domains score								
Low (1 to <2)	100.0^{E}	100.0^{E}	100.0^{E}	–	50.0^{ABC}	–	–	–
Medium (2 to <3)	0.0^{E}	0.0^{E}	0.0^{E}	–	50.0^{ABC}	–	–	–
High (3)	0.0	0.0	0.0	–	0.0	–	–	–
Number of children	**3**	**2**	**5**	**0**	**2**	**0**	**0**	**0**
CFARS overall score								
Low (1 to <2)	81.1	67.3^{CEGH}	83.5^{B}	76.2	83.9^{B}	75.0	83.8^{B}	84.2^{B}
Medium (2 to <3)	18.9	32.7^{CEGH}	16.5^{B}	23.8	16.1^{B}	25.0	16.2^{B}	15.8^{B}
High (3)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Number of children	**95**	**101**	**310**	**21**	**186**	**8**	**37**	**19**
CFARS security domains score								
1 to <2 – Low (%)	95.8^{CDFGH}	89.1^{DF}	87.7^{ADF}	76.2^{ABCE}	90.9^{DF}	75.0^{ABCE}	83.8^{A}	84.2^{A}
2 to <3 – Medium (%)	4.2^{CDFGH}	9.9^{DF}	11.6^{ADF}	23.8^{ABCE}	9.1^{DF}	25.0^{ABCE}	16.2^{A}	15.8^{A}
3 – High (%)	0.0	1.0	0.6	0.0	0.0	0.0	0.0	0.0
Number of children	**95**	**101**	**310**	**21**	**186**	**8**	**37**	**19**
ASAM recommended level of care [a]								
Intervention (1 to <2)	50.0^{BCDFG}	19.0^{ADEFH}	30.0^{AEFGH}	33.3^{ABEFGH}	60.0^{BCDFG}	0.0^{ABCDEGH}	11.1^{ACDEFH}	50.0^{BCDFG}
Methadone/ medication maintenance (2 to <3)	7.1^{DFGH}	14.3^{DFGH}	8.3^{DFGH}	0.0^{ABCE}	5.0^{DFGH}	0.0^{ABCE}	0.0^{ABCE}	0.0^{ABCE}

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Outpatient detox (3 to <4)	0.0[CEH]	0.0[CEH]	10.0[ABDEFG]	0.0[CEH]	5.0[ABCDFG]	0.0[CEH]	0.0[CEH]	10.0[ABDFG]
Regular outpatient treatment (4 to <5)	14.3[BDFGH]	42.9[ACEF]	20.0[BDFGH]	50.0[ACEFH]	20.0[BDFGH]	0.0[ABCDEGH]	44.4[ACEFH]	30.0[ACDEFG]
Intensive outpatient/day treatment (5 to <6)	7.1[DF]	9.5[DF]	5.0[DEF]	0.0[ABCEGH]	10.0[CDF]	0.0[ABCEGH]	11.1[DF]	10.0[DF]
Residential detox (6 to <7)	7.1[CDEFGH]	14.3[EFGH]	21.7[AEFGH]	16.7[AEFGH]	0.0[ABCDFG]	100.0[ABCDEGH]	33.3[ABCDEFH]	0.0[ABCDFG]
Residential (7)	14.3[BCDEFGH]	0.0[AC]	5.0[ABDEFGH]	0.0[AC]	0.0[AC]	0.0[AC]	0.0[AC]	0.0[AC]
Number of children	**14**	**21**	**60**	**6**	**20**	**1**	**9**	**10**
ASAM placement level of care[a]								
Intervention (1 to <2)	50.0[BCDFG]	19.0[AEFH]	28.3[ADEFGH]	16.7[ACEFH]	55.0[BCDFG]	0.0[ABCDEGH]	11.1[ACEFH]	50.0[BCDFG]
Methadone/ medication maintenance (2 to <3)	7.1[DFGH]	4.8	8.3[DFGH]	0.0[ACE]	5.0[DFGH]	0.0[ACE]	0.0[ACE]	0.0[ACE]
Outpatient detox (3 to <4)	7.1[BDEFH]	0.0[ACG]	8.3[BDEFH]	0.0[ACG]	0.0[ACG]	0.0[ACG]	11.1[BDEFH]	0.0[ACG]
Regular outpatient treatment (4 to <5)	7.1[BCDEFGH]	52.4[ACEFG]	25.0[ABDFH]	66.7[ACEFGH]	30.0[ABDF]	0.0[ABCDEGH]	33.3[ABDF]	40.0[ACDF]
Intensive outpatient/day treatment (5 to <6)	7.1[DFGH]	9.5[DFGH]	3.3[DEFGH]	0.0[ABCEG]	10.0[CDFGH]	0.0[ABCEG]	22.2[ABCDEFH]	0.0[ABCEG]
Residential detox (6 to <7)	14.3[DEF]	14.3[DEF]	21.7[DEFH]	0.0[ABCFGH]	0.0[ABCFGH]	100.0[ABCDEGH]	22.2[DEFH]	10.0[CDEFG]
Residential (7)	7.1[BDEFGH]	0.0[ACD]	5.0[BDEFGH]	16.7[ABCEFGH]	0.0[ACD]	0.0[ACD]	0.0[ACD]	0.0[ACD]
Number of children	**14**	**21**	**60**	**6**	**20**	**1**	**9**	**10**
OCW investigation risk level								
Low (1 to <2)	3.8[F]	4.9	2.5[F]	0.6	2.9[F]	0.0[ACE]	2.4	1.5
Moderate (2 to <3)	22.0[F]	23.0[F]	28.2[F]	22.4[F]	21.1[F]	50.0[ABCDEGH]	23.2[F]	28.1[F]
High (3 to <4)	55.9[F]	54.1[F]	52.7[F]	59.0[F]	60.4[F]	25.0[ABCDEGH]	50.6[F]	50.9[F]
Very high (4)	18.3	18.0	16.6	17.9	15.6	25.0	23.8	19.5
Number of children	**186**	**61**	**433**	**156**	**346**	**16**	**164**	**267**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: The n value is the number of children with any nonmissing assessment scores. For children in Florida who had more than one assessment record, the average score for the child was used for estimates.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

[a]ASAM score corresponds to category of recommended or actual care, ordered by intensity of care. Average score was used to allocate children to categories. Consequently, the average should be interpreted with caution, since an average score of 4 to <5 (regular outpatient treatment) may not contain any regular outpatient placements (for example, it could contain an equal number of outpatient detox and residential detox placements).

D.29. Florida classes: Child welfare history prior to study window

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Prior child welfare history								
Prior investigations	53.9[BDEH]	77.1[ACDFGH]	58.8[BDEH]	27.0[ABCEFG]	82.9[ACDFGH]	51.4[BDEH]	54.7[BDEH]	33.3[ABCEFG]
Prior child welfare custodial episode	10.3[BDE]	55.2[ACDFGH]	10.8[BDEG]	3.9[ABCE]	58.3[ACDFGH]	9.5[BE]	4.0[BCE]	6.7[BE]
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Prior episodes and prior investigations include episodes or investigations that started prior to the study window. The count of prior investigations excludes any investigations that are associated with an episode that began during the study window. The number of episodes and placements includes ones that are right-censored, meaning they are ongoing at the end of the study time period.

In Florida, an episode is defined by any period of time in in-home or out-of-home care. Florida estimates reported in the include episodes composed entirely of in-home placements.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level
[B]Difference between Class 2 is statistically significant at the 0.05 level
[C]Difference between Class 3 is statistically significant at the 0.05 level
[D]Difference between Class 4 is statistically significant at the 0.05 level
[E]Difference between Class 5 is statistically significant at the 0.05 level
[F]Difference between Class 6 is statistically significant at the 0.05 level
[G]Difference between Class 7 is statistically significant at the 0.05 level
[H]Difference between Class 8 is statistically significant at the 0.05 level

D.30. Florida classes: Permanency

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Exited custody	49.9^{F}	42.3	52.7^{FH}	55.4^{FH}	45.6^{F}	27.1^{ACDE}	41.3	39.1^{CD}
Remained in custody	49.3^{F}	57.7	46.2^{FH}	44.6^{FH}	53.6^{F}	72.9^{ACDE}	58.4	59.8^{CD}
Missing	0.8	0.0	1.0	0.0	0.8	0.0	0.3	1.0
Permanency outcome among children who exited custody								
Reunification	50.6^{CDEFGH}	45.9^{CDEFGH}	69.3^{ABFG}	64.9^{ABFG}	61.8^{ABFG}	$12.3^{ABCDEGH}$	$88.1^{ABCDEFH}$	70.1^{ABFG}
Guardianship	25.3^{DG}	16.5^{G}	17.1^{DG}	6.6^{ACEFH}	21.6^{DG}	28.1^{DG}	3.0^{ABCEFH}	17.1^{DG}
Adoption	15.7^{BCDFGH}	29.4^{ACEFGH}	3.7^{ABDEF}	27.5^{ACEFGH}	13.3^{BCDFG}	$57.9^{ABCDEGH}$	1.5^{ABDEFH}	8.0^{ABDFG}
Aged out or emancipated	5.4^{D}	7.1	7.5^{DEF}	0.5^{ACGH}	2.7^{C}	1.8^{C}	6.7^{D}	4.3^{D}
Death	0.4	0.0	0.4	0.0	0.0	0.0	0.0	0.0
Other	2.7^{F}	1.2	2.0^{F}	0.5	0.6	0.0^{AC}	0.7	0.5
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit. Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.31. Florida classes: Average time to permanency (days)

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Exited custody	287.0[BCDFGH]	421.9[ACDEFGH]	224.7[ABDFG]	348.8[ABCEFGH]	245.8[BDFG]	605.8[ABCDEGH]	171.4[ABCDEF]	218.6[ABDF]
Permanency outcome among children who exited custody								
Reunification	221.1[BFG]	337.9[ACEGH]	174.5[BDF]	272.8[CEFGH]	192.6[BDF]	514.7[ACDEGH]	156.2[ABDF]	177.4[BDF]
Guardianship	332.6[DF]	437.6[H]	335.4[DF]	464.8[ACEH]	334.9[DF]	565.3[ACEH]	513.8[H]	284.3[BDFG]
Adoption	459.8[EF]	556.6[E]	446.2[F]	496.0[EF]	349.2[ABDF]	643.1[ACDEH]	381.0	462.7[F]
Aged out or emancipated	268.6	355.0	302.3	776.0[GH]	232.3	660.0	191.3[D]	162.8[D]
Death	8.0	–	404.0	–	–	–	–	–
Other	163.3	514.0	279.4	170.0	294.5	–	3.0	292.0

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: If a child had more than one episode, the final episode was used to identify permanency type and identify length of stay until permanency exit.

Permanency is defined as having exited out-of-home care by the end of the study window. If a child exited out-of-home care and was in an in-home placement by the end of the study window, this child is considered to have exited care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

D.32. Florida classes: Number of foster care episodes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Number of child welfare episodes over the life of the child								
One episode	80.5^{BDEG}	$25.9^{ACDEFGH}$	83.5^{BDEG}	92.9^{ABCEF}	$0.0^{ABCDFGH}$	78.1^{BDEG}	91.7^{ABCEF}	86.8^{BE}
Two episodes	15.9^{BDEG}	$46.8^{ACDEFGH}$	13.5^{BDEG}	5.2^{ABCEF}	$67.3^{ABCDFGH}$	17.6^{BDEG}	6.4^{ABCEF}	12.1^{BE}
Three episodes	3.1^{BE}	19.9^{ACDFGH}	2.8^{BE}	1.3^{BE}	23.2^{ACDFGH}	3.3^{BE}	1.8^{BE}	1.0^{BE}
Four or more episodes	0.6^{E}	7.5^{CGH}	0.2^{BE}	0.5^{E}	9.4^{ACDFGH}	1.0^{E}	0.0^{BE}	0.0^{BE}
Number of child welfare episodes during the study window								
One episode	89.5^{BDE}	$69.2^{ACDEFGH}$	93.1^{BE}	96.3^{ABEF}	$39.4^{ABCDFGH}$	84.8^{BDE}	94.8^{BE}	92.9^{BE}
Two episodes	10.3^{BDE}	27.9^{ACDEGH}	6.5^{BE}	3.7^{ABEF}	$55.5^{ABCDFGH}$	14.8^{DEG}	4.6^{BEF}	7.1^{BE}
Three episodes	0.2^{E}	2.5	0.5^{E}	0.0^{E}	4.5^{ACDFGH}	0.5^{E}	0.6^{E}	0.0^{E}
Four or more episodes	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: In Florida, an episode is defined by any period of time in in-home or out-of-home care. Florida estimates reported in the include episodes composed entirely of in-home placements.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.33. Florida classes: Average number of foster care placement moves across all custody episodes

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Mean	4.2^{BDE}	$18.4^{ACDEFGH}$	4.2^{BDEH}	$6.4^{ABCEFGH}$	$7.9^{ABCDFGH}$	3.0^{BDE}	3.1^{BDE}	2.9^{BCDE}
Median	3.0	13.0	3.0	5.0	6.0	3.0	3.0	2.0
Min	1.0	3.0	1.0	3.0	2.0	1.0	1.0	1.0
Max	76.0	115.0	70.0	53.0	108.0	16.0	13.0	34.0
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Statistics other than the mean were not tested for significance, so the absence of significance flags does not indicate the absence of significant differences.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.34. Florida classes: Share of time spent in family foster care or group/residential care

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Family foster care								
Mean	72.4$^{\text{BCEFG}}$	52.9$^{\text{ADEFGH}}$	59.8$^{\text{ADEFGH}}$	69.8$^{\text{BCFGH}}$	64.8$^{\text{ABCFGH}}$	92.4$^{\text{ABCDEGH}}$	27.7$^{\text{ABCDEFH}}$	76.9$^{\text{BCDEFG}}$
Median	83.9	54.8	65.6	76.6	65.3	99.3	4.7	97.9
Min	0.0	0.0	0.0	0.0	1.3	25.6	0.0	0.0
Max	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Group or residential care								
Mean	5.2$^{\text{BCG}}$	19.2$^{\text{ACDEFGH}}$	11.3$^{\text{ABDEFGH}}$	4.4$^{\text{BCG}}$	3.3$^{\text{BCG}}$	0.8$^{\text{BCG}}$	46.9$^{\text{ABCDEFH}}$	1.5$^{\text{BCG}}$
Median	0.0	10.2	0.0	0.0	0.0	0.0	37.9	0.0
Min	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0
Max	100.0	100.0	100.0	80.2	53.1	44.5	100.0	65.2
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: The average share of time spent in custody by placement type is calculated as the ratio of days spent in a specific placement type over total days spent in custody for each child. Placements with missing start or end dates or missing placement type are excluded from the analysis. As a result, these estimates may underestimate time in each placement type.

Family foster care includes the following placement types: foster family home (non-relative), foster family home (relative), pre-adoptive home, and relative. Group or residential care includes the following placement types: group home, institution, and residential treatment. The distribution is calculated across all children in custody, including children who were not in foster care/group care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

$^{\text{A}}$Difference between Class 1 is statistically significant at the 0.05 level

$^{\text{B}}$Difference between Class 2 is statistically significant at the 0.05 level

$^{\text{C}}$Difference between Class 3 is statistically significant at the 0.05 level

$^{\text{D}}$Difference between Class 4 is statistically significant at the 0.05 level

$^{\text{E}}$Difference between Class 5 is statistically significant at the 0.05 level

$^{\text{F}}$Difference between Class 6 is statistically significant at the 0.05 level

$^{\text{G}}$Difference between Class 7 is statistically significant at the 0.05 level

$^{\text{H}}$Difference between Class 8 is statistically significant at the 0.05 level

D.35. Florida classes: Children receiving child welfare CBC-purchased services from Eckerd

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Children receiving child welfare CBC-purchased services	100.0[BCDEFGH]	88.6[ACDEFGH]	12.7[ABFH]	16.8[ABFH]	16.9[ABFH]	32.4[ABCDEGH]	9.8[ABF]	6.1[ABCDEF]
Among children receiving child welfare CBC-purchased services:								
Children receiving CBC-purchased custodial services	86.8[DF]	94.4[C]	85.5[BDFH]	95.3[ACEF]	88.8[DF]	100.0[ACDEGH]	87.5[F]	93.1[CF]
Children receiving CBC-purchased noncustodial services	21.0[DFH]	15.7[F]	21.8[DFH]	7.8[ACEF]	17.6[DFH]	1.5[ABCDEGH]	15.6[FH]	6.9[ACEFG]
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Child welfare services for Florida are CBC-purchased services provided by Eckerd. Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

D.36. Florida classes: Average number of child welfare CBC-purchased services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Average number of child welfare CBC-purchased services received per child	2.3^{BCDE}	3.1^{ACDEFGH}	1.4^{AB}	1.4^{AB}	1.5^{AB}	1.6^{B}	1.3^{B}	1.2^{B}
Among children receiving child welfare CBC-purchased services:								
Average number of CBC-purchased custodial services received per child	2.1^{BCE}	3.1^{ACDEFGH}	1.3^{AB}	1.3^{B}	1.4^{AB}	1.6^{B}	1.3^{B}	1.1^{B}
Average number of CBC-purchased noncustodial services received per child	2.4	1.5	1.1	1.2	1.2	1.0	1.2	2.0
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Child welfare services for Florida are CBC-purchased services provided by Eckerd. Custodial services are defined as services that started while an out-of-home placement was in progress. Noncustodial services are defined as services that started while an out-of-home placement was not in progress (this could be during an in-home placement or during a period of time when no placements were in progress). Children can receive both custodial and noncustodial services.

Distributions calculated across those receiving services.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level
^{B}Difference between Class 2 is statistically significant at the 0.05 level
^{C}Difference between Class 3 is statistically significant at the 0.05 level
^{D}Difference between Class 4 is statistically significant at the 0.05 level
^{E}Difference between Class 5 is statistically significant at the 0.05 level
^{F}Difference between Class 6 is statistically significant at the 0.05 level
^{G}Difference between Class 7 is statistically significant at the 0.05 level
^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.37. Florida classes: Number and type of child welfare CBC-purchased services from Eckerd for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Children receiving child welfare CBC-purchased services	100.0^{BCDEFGH}	88.6^{ACDEFGH}	12.7^{ABFH}	16.8^{ABFH}	16.9^{ABFH}	32.4^{ABCDEGH}	9.8^{ABF}	6.1^{ABCDEF}
Among children receiving child welfare CBC-purchased services:								
One service	53.0^{CDEGH}	38.2^{CDEGH}	68.2^{ABH}	68.8^{ABH}	67.2^{ABGH}	55.9^{GH}	78.1^{ABEFH}	89.7^{ABCDEFG}
Two services	20.1^{H}	18.5^{H}	25.5^{GH}	26.6^{GH}	22.4^{GH}	29.4^{GH}	12.5^{CDEFH}	3.4^{ABCDEFG}
Three services	27.0^{BCDEFGH}	43.3^{ACDEFGH}	6.4^{AB}	4.7^{AB}	10.4^{AB}	14.7^{AB}	9.4^{AB}	6.9^{AB}
Among children receiving child welfare CBC-purchased services:								
Assessments	21.8^{BDFGH}	39.3^{ACDEFH}	21.8^{BDFGH}	0.0^{ABCEGH}	21.6^{BDFGH}	4.4^{ABCEG}	43.8^{ACDEFH}	3.4^{ABCDEG}
Documentation services	13.6^{CDH}	15.2	23.6^{AG}	25.0^{AG}	18.4	25.0	12.5^{CDH}	24.1^{AG}
Putative father registry	13.4^{DFGH}	11.2^{DFGH}	8.2^{DFGH}	28.1^{ABCEG}	12.8^{DFGH}	42.6^{ABCEGH}	0.0^{ABCDEFH}	27.6^{ABCEFG}
Family/caregiver support services	12.6^{D}	11.8^{D}	10.9^{D}	26.6^{ABCEFG}	15.2^{DG}	11.8^{D}	6.3^{DEH}	17.2^{G}
Therapy/counseling	17.4^{CDEFGH}	19.7^{CDEFGH}	4.5^{AB}	4.7^{AB}	6.4^{AB}	5.9^{AB}	6.3^{AB}	3.4^{AB}
Child care assistance	8.4^{H}	12.4^{H}	3.6^{H}	9.4^{H}	5.6^{H}	5.9	3.1	0.0^{ABCDE}
Housing assistance	6.9^{G}	9.0	7.3^{G}	6.3^{G}	10.4^{F}	2.9^{EG}	15.6^{ACDFH}	6.9^{G}
Transportation assistance	7.6^{DGH}	11.2^{DGH}	6.4^{DGH}	0.0^{ABCE}	4.8^{DGH}	4.4	0.0^{ABCE}	0.0^{ABCE}
Health services	4.6	8.4	6.4	6.3	5.6	7.4	6.3	3.4
Youth Support Services	4.0^{GH}	7.9^{GH}	5.5^{DGH}	1.6^{C}	2.4^{GH}	1.5	0.0^{ABCE}	0.0^{ABCE}
Education Supports	4.4	3.9	2.7	0.0	4.0	2.9	6.3	0.0
Caregiver/parenting education	3.8^{FGH}	2.8	1.8^{FGH}	1.6	1.6	0.0^{AC}	0.0^{AC}	0.0^{AC}
Substance abuse testing/treatment	2.3	2.8	4.5^{GH}	3.1	3.2^{GH}	1.5	0.0^{CE}	0.0^{CE}
Supervised Visitation	1.0	2.8	0.9	0.0	0.8	0.0	0.0	0.0
Mentoring	0.2	0.6	0.9	0.0	0.0	0.0	0.0	0.0
Case management	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Language/interpretation Services	0.2	0.6	0.0	0.0	0.0	0.0	0.0	0.0
Respite	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0
Legal services	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other[a]	20.1	26.4^{DE}	18.2^{H}	12.5^{BH}	12.8^{BH}	19.1	18.8	27.6^{CDE}

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Among children receiving child welfare services:								
One category of services	69.8^{BGH}	$46.6^{ACDEFGH}$	75.5^{BH}	76.6^{BH}	76.0^{BH}	73.5^{BH}	81.3^{AB}	89.7^{ABCDEF}
Two categories of services	21.2^{H}	30.9^{H}	21.8^{H}	21.9^{H}	22.4^{H}	17.6	18.8^{H}	6.9^{ABCDEG}
Three or more categories of services	9.0^{BCDEG}	$22.5^{ACDEFGH}$	2.7^{ABG}	1.6^{AB}	1.6^{AB}	8.8^{BG}	0.0^{ABCFH}	3.4^{BG}
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Child welfare services for Florida are CBC-purchased services provided by Eckerd.

[a]Other services include autism spectrum, behavioral assistance, Community Kids, IV-E waiver stipend, nonspecific to any area, other, paternity testing, reimbursement, Restorative Justice Program, shipping of luggage, state institutional claim, and uninsured children.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.38. Florida classes: Children receiving Medicaid services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Medicaid services	95.6[DGH]	97.5[DG]	98.4[DEGH]	86.1[ABCH]	93.1[CH]	91.0[H]	85.3[ABCH]	100.0[ACDEFG]
Inpatient services	16.4[BC]	55.2[ACDEFGH]	33.2[ABDEFGH]	21.5 [BC]	13.0 [BC]	18.1[BC]	11.3[BCH]	20.9[BCG]
Physical health	77.9[BCDEFGH]	39.6[ACDEFGH]	58.9[ABDFH]	96.3[ABCEFG]	67.7[ABDFH]	100.0[ABCDEGH]	62.2[ABDFH]	92.0[ABCEFG]
Behavioral health	25.6[BCDEFGH]	77.5[ACDEFGH]	48.8[ABDEFH]	3.7[ABCEG]	36.5[ABCDFH]	2.6[ABCEG]	45.9[ABDFH]	9.0[ABCEG]
Outpatient services	95.2[DGH]	97.0[DG]	98.2[DEG]	85.3[ABCEH]	93.0[CDGH]	91.0[H]	83.8[ABCEH]	99.4[ADEFG]
Physical health	98.8	98.5	98.2[D]	100.0[C]	99.0	99.5	96.0	98.7
Behavioral health	64.1[BCDEFH]	91.3[ACDEFGH]	77.4[ABDFH]	29.8[ABCEG]	79.7[ABDFH]	41.4[ABCEG]	72.3[BDFH]	37.7[ABCEG]
Emergency services	64.6[BH]	84.1[ACDEFGH]	71.6[BDGH]	53.0[BCEH]	70.6[BDGH]	60.5[BH]	56.6[BCEH]	100.0[ABCDEFG]
Physical health	99.7	97.6	99.5	100.0	99.8	100.0	100.0	100.0
Behavioral health	5.0[BC]	29.0[ACDEFGH]	10.7[ABDEFH]	2.0[BC]	4.0[BC]	1.6[BC]	5.4[B]	2.5[BC]
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

D.39. Florida classes: Number and type of Medicaid services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Average number of inpatient services per child	3.3	4.8^{H}	3.6	2.1	2.6	1.7	2.6	2.1^{B}
Physical health	2.0	1.9	2.3	1.5	1.7	1.5	1.3	1.9
Behavioral health	6.8	5.2	4.7^{D}	19.7^{CE}	3.9^{D}	6.0	3.9	4.2
Average number of outpatient services per child	26.3^{BCDEH}	$80.3^{ACDEFGH}$	38.8^{ABDFGH}	18.0^{ABCE}	33.3^{ABDGH}	25.6^{BC}	24.6^{BCE}	17.4^{ABCE}
Physical health	10.6^{DFH}	13.4^{G}	12.0^{FG}	14.0^{AEG}	11.5^{DFGH}	16.6^{ACEG}	8.3^{BCDEFH}	13.7^{AEG}
Behavioral health	24.8^{BCH}	$73.6^{ACDEFGH}$	34.9^{ABDGH}	13.4^{BC}	27.5^{BH}	22.1^{B}	23.1^{BC}	10.3^{ABCE}
Average number of emergency services per child	3.1^{BCH}	5.2^{ACDEFG}	3.9^{ABDEFH}	2.8^{BCH}	3.1^{BCH}	2.8^{BCH}	3.3^{BH}	5.0^{ACDEFG}
Physical health	3.0^{BH}	4.7^{ACDEFG}	3.7^{BDEH}	2.8^{BCH}	3.1^{BCH}	2.7^{BH}	3.2^{BH}	4.9^{ACDEFG}
Behavioral health	1.5	2.0	1.8	1.0	1.1	1.5	2.4	1.2

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Note: Distributions calculated across those receiving services.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

^{A}Difference between Class 1 is statistically significant at the 0.05 level

^{B}Difference between Class 2 is statistically significant at the 0.05 level

^{C}Difference between Class 3 is statistically significant at the 0.05 level

^{D}Difference between Class 4 is statistically significant at the 0.05 level

^{E}Difference between Class 5 is statistically significant at the 0.05 level

^{F}Difference between Class 6 is statistically significant at the 0.05 level

^{G}Difference between Class 7 is statistically significant at the 0.05 level

^{H}Difference between Class 8 is statistically significant at the 0.05 level

D.40. Florida classes: Children receiving SAMH services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Any SAMH service per child	19.1[BCDFH]	62.2[ADEFGH]	50.6[ADEFGH]	3.1[ABCEG]	25.9[BCDFGH]	5.2[ABCE]	14.1[BCDE]	6.1[ABCE]
Substance abuse services[a]	5.5[BCF]	28.4[ADEFGH]	15.7[ADEFGH]	1.3[BCE]	6.6[BCDF]	1.0[ABCE]	6.1[BC]	3.1[BC]
24-hour services	6.9[DEF]	1.8[DG]	5.9[DEF]	20.0[ABCEFGH]	2.0[ACDFG]	0.0[ACDEGH]	10.0[BDEF]	6.7[DF]
Acute services	10.3[BCDFH]	22.8[ADEF]	17.6[ADEF]	40.0[ABCEFGH]	8.2[BCDFH]	0.0[ABCDEGH]	15.0[DF]	20.0[ADEF]
Outpatient services	89.7[CDEF]	94.7[D]	96.3[ADF]	80.0[ABCEFGH]	95.9[ADF]	100.0[ACDEGH]	95.0[DF]	93.3[DF]
Mental health services[a]	16.4[BCDFH]	57.2[ADEFGH]	45.7[ADEFGH]	1.8[ABCEG]	23.6[BCDFGH]	4.3[ABCE]	10.4[BCDE]	4.2[ABCE]
24-hour services	2.3	5.2	1.5	0.0[H]	0.6[H]	0.0[H]	2.9	5.0[DEF]
Acute services	15.1[BDG]	40.9[ACEFGH]	17.7[BDG]	42.9[ACEFGH]	16.0[BDG]	11.1[BD]	5.9[ABCDEH]	20.0[BDG]
Outpatient services	96.5[DFH]	93.9	94.9[DFH]	85.7[ACEFGH]	96.0[DFH]	100.0[ACDE]	97.1[D]	100.0[ACDE]
Number of children	**523**	**201**	**865**	**381**	**741**	**210**	**327**	**478**

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Notes: Distributions are calculated across those receiving services.

Services are denominated in treatment episodes. Multiple treatment episodes can occur at the same time. Counts of services by subtype of care are counts of treatment episodes that included each subtype of care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level
[B]Difference between Class 2 is statistically significant at the 0.05 level
[C]Difference between Class 3 is statistically significant at the 0.05 level
[D]Difference between Class 4 is statistically significant at the 0.05 level
[E]Difference between Class 5 is statistically significant at the 0.05 level
[F]Difference between Class 6 is statistically significant at the 0.05 level
[G]Difference between Class 7 is statistically significant at the 0.05 level
[H]Difference between Class 8 is statistically significant at the 0.05 level

[a]24-hour services include residential treatment care levels 1–4, room & board with supervision levels 1–3, and short-term residential treatment. Acute care includes crisis stabilization, crisis support/emergency, inpatient, and substance abuse detoxification. Outpatient includes all other services, for example, assessment, intervention, outreach, prevention, methadone maintenance, FACT team, etc.

D.41. Florida classes: Number and type of SAMH services for those receiving services

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
Any SAMH service per child	1.9[B]	4.4[ACEFG]	2.4[B]	2.8	2.0[B]	1.5[B]	2.3[B]	2.9
Substance abuse services[a]	1.7	3.9	2.6	4.0	1.8	1.0	2.3	2.1
24-hour services	1.5	1.0	1.3	1.0	1.0	–	2.5	2.0
Acute services	1.0	1.4	1.2	1.0	1.0	–	1.3	1.0
Outpatient services	1.7	3.9	2.6	4.8	1.8	1.0	2.2	1.9
Mental health services[a]	1.6[B]	2.8[ACEG]	1.7[B]	2.0	1.6[B]	1.6	1.7[B]	2.6
24-hour services	1.0	1.5	1.0	–	1.0	–	1.0	1.0
Acute services	1.8	2.2	2.1	1.0	1.5	1.0	5.0	2.0
Outpatient services	1.4[BH]	2.0[ACEG]	1.4[BH]	2.0	1.5[BH]	1.4	1.5[B]	2.2[ACE]

Source: Florida OCW; Florida AHCA data; Florida Eckerd; Florida SAMH.

Notes: Distributions are calculated across those receiving services.

Services are denominated in treatment episodes. Multiple treatment episodes can occur at the same time. Counts of services by subtype of care are counts of treatment episodes that included each subtype of care.

Statistical testing of all pairwise comparisons for each variable was conducted. The estimates provided for a given class were compared to all others and if a pairwise difference was statistically significant, this was labeled using the following key:

[A]Difference between Class 1 is statistically significant at the 0.05 level

[B]Difference between Class 2 is statistically significant at the 0.05 level

[C]Difference between Class 3 is statistically significant at the 0.05 level

[D]Difference between Class 4 is statistically significant at the 0.05 level

[E]Difference between Class 5 is statistically significant at the 0.05 level

[F]Difference between Class 6 is statistically significant at the 0.05 level

[G]Difference between Class 7 is statistically significant at the 0.05 level

[H]Difference between Class 8 is statistically significant at the 0.05 level

[a]24-hour services include residential treatment care levels 1–4, room & board with supervision levels 1–3, and short-term residential treatment. Acute care includes crisis stabilization, crisis support/emergency, inpatient, and substance abuse detoxification. Outpatient includes all other services, for example, assessment, intervention, outreach, prevention, methadone maintenance, FACT team, etc.

APPENDIX E

PREDICTIVE MODELING

This page has been left blank for double-sided copying.

TABLES

FIGURES

This page has been left blank for double-sided copying.

In this appendix, we elaborate on our approach to estimating and finalizing the models used to predict superutilization based on the number of placement moves in Florida and Tennessee. First, we describe the list of predictors used in both sites to predict superutilization. Next, we provide an overview of the multistep process to estimate, examine, and select the final models presented in the report. Finally, we discuss the interpretation of the model results.

A. Predictors

Our proposed approach to the predictive analysis was to use a pre-specified set of covariates from the lookback period (that is, the year prior to the prediction episode) and from the child welfare history of the child (that is, variables collected earlier than a year prior to the prediction episode) as well as regional or county-level variables, to predict superutilization on the number of placement moves. We define superutilization as having an observed number of placement moves greater than or equal to the 90th percentile number for each respective study site. In the tables below we summarize, by site, the full list of variables included in the final predictive models for Tennessee and Florida, describing the continuous and binary predictors separately to provide information specific to their distributional characteristics.

1. Predictors used in the final model for Tennessee

In total, the final model for Tennessee included 65 predictors. We describe the distributions of these predictors in Tables E.1 (continuous predictors) and E.2 (binary predictors), as well as VIII.2 for certain demographic characteristics (gender and race/ethnicity).

E.1. Tennessee continuous predictors

	Distribution				
	Mean	Standard deviation	Minimum	Maximum	Number of missing
Demographic[a]					
Age at entry into out-of-home custody	7.9	5.9	0	23	5
Investigations					
Number of prior child welfare investigations	2.4	3.1	0	29	0
Placements					
Number of child welfare placement moves in lookback year	0.1	0.4	0	11	0
Average percentage of time in group/congregate care in lookback year	0.2	3.9	0	100	0
Episodes					
Number of prior child welfare custodial episodes	0.2	0.4	0	5	0
Total length of stay in days in prior custodial episodes	57.7	232.2	0	5,155	0
Child welfare services					
Number of custodial child welfare services in lookback year	0.1	0.5	0	24	0
Number of noncustodial child welfare services in lookback year	0.3	1.1	0	21	0

	Distribution				
	Mean	Standard deviation	Minimum	Maximum	Number of missing
Assessments					
Average CANS assessment result in lookback year	1.8	1.0	1	4	11,707
Average FAST assessment result in lookback year	1.4	0.6	1	3	9,222
Average YLS assessment result in lookback year	12.5	5.8	3	32	11,964
Average Ansell-Casey Life Skills assessment result in lookback year	39.0	36.7	2	100	11,858
Medicaid services					
Medicaid inpatient behavioral health services in lookback year	0.1	0.3	0	7	0
Medicaid inpatient physical health services in lookback year	0.1	0.3	0	7	0
Medicaid outpatient behavioral health services in lookback year	2.7	11.0	0	208	0
Medicaid outpatient physical health services in lookback year	2.3	3.4	0	47	0
Medicaid emergency behavioral health services in lookback year	0.0	0.3	0	8	0
Medicaid emergency physical health services in lookback year	0.8	1.5	0	27	0
DCS region composition[b]					
Percent white	82.2	16.6	40	96	1,652
Percent black	13.0	15.3	1	53	1,652
Percent Hispanic	4.5	1.8	2	10	1,652
Percent Asian	1.4	0.9	0	3	1,652
Percent American Indian/Alaska Native	0.3	0.0	0	0	1,652
Percent Native Hawaiian/Pacific Islander	0.0	0.1	0	0	1,652
Percent multiracial	1.9	0.4	1	3	1,652
Percent other	1.2	0.9	0	4	1,652
Percentage of married households	49.5	6.0	37	58	1,652
Percent foreign born	4.3	2.4	2	12	1,652
Percentage of high school graduates	85.2	3.2	81	90	1,652
Percent unemployed	8.5	1.3	6	11	1,652
Percent living under poverty line	18.0	3.0	11	21	1,652
Percent urban	62.0	22.9	32	97	1,652
Percent rural	38.0	22.9	3	68	1,652

Source: Tennessee DCS; TennCare; American Community Survey 2015; Census 2010.

[a]Other binary demographics, including race and gender, were included in the predictive model. The distribution of these variables can be found in VIII.2.

[b]DCS region-level information was created by aggregating county-level 2015 5-year American Community Survey and 2010 Census data.

E.2. Tennessee binary predictors

	Number of children	Percentage of children	Number of missing
Reason for removal:			
Drug abuse (parent)	4,614	38.3	0
Neglect (alleged/reported)	4,373	36.3	0
Child's behavioral problem	1,519	12.6	0
Physical abuse	1,344	11.1	0
Abandonment	1,245	10.3	0
Incarceration of parent(s)	1,118	9.3	0
Inadequate housing	1,068	8.9	0
Caretaker inability to cope due to illness or other reasons	956	7.9	0
Sexual abuse	606	5.0	0
Truancy	457	3.8	0
Alcohol abuse (parent)	302	2.5	0
Drug abuse (child)	238	2.0	0
Relinquishment	157	1.3	0
Death of parent(s)	114	0.9	0
Child's disability	71	0.6	0
Alcohol abuse (child)	31	0.3	0
Neonatal abstinence syndrome (NAS) prosecution	1	0.0	0
Average recommended service level across investigations prior to episode[a]			
Average service level of 1	761	6.3	0
Average service level of 2	873	7.2	0
Average service level of 3	2,748	22.8	0
Average service level missing	6,309	52.3	0
Missing investigation record	1,365	11.3	0

Source: Tennessee DCS; TennCare.

[a]Investigations were classified as: (1) no services needed; (2) services recommended; and (3) services required. Among those with missing investigation service level information were children whose investigation preceding the t0 episode could not be identified (missing investigation record) and those whose investigation(s) preceding the t0 episode had missing service level information. We classified these two groups of missing values into distinct categories.

2. Predictors used in the final model for Florida

The final Florida model included 55 predictors. Their distributional characteristics are described in Tables E.3 (continuous predictors), E.4 (binary predictors), and VIII.2 (gender and race/ethnicity).

E.3. Florida continuous predictors

	Distribution				
	Mean	Standard deviation	Minimum	Maximum	Number of missing
Demographic[a]					
Age at entry into out-of-home custody	6.1	5.2	0	18	3
Investigations					
Number of prior child welfare investigations	2.1	2.4	0	18	0
Placements					
Number of child welfare placement moves in lookback year	0.2	0.6	0	24	0
Average percentage of time in group/residential care in lookback year	0.2	4.0	0	100	0
Episodes					
Number of prior child welfare episodes	0.3	0.6	0	9	0
Total length of stay in days in prior out-of-home foster care placements	153.8	377.3	0	5,028	0
Assessments					
Average CFARS assessment level in lookback year	1.3	0.5	1	3	7,795
Average CFARS security level in lookback year	1.2	0.4	1	3	7,795
Average ASAM recommended level of care in lookback year	2.8	1.8	1	7	8,225
Average ASAM placement level in lookback year	2.8	1.8	1	6	8,225
Medicaid services					
Medicaid inpatient behavioral health services in lookback year	0.0	0.7	0	36	0
Medicaid inpatient physical health services in lookback year	0.1	0.6	0	26	0
Medicaid outpatient behavioral health services in lookback year	0.8	7.7	0	357	0
Medicaid outpatient physical health services in lookback year	1.7	2.8	0	37	0
Medicaid emergency behavioral health services in lookback year	0.0	0.1	0	4	0
Medicaid emergency physical health services in lookback year	0.5	1.0	0	13	0
SAMH					
SAMH mental health services in lookback year	0.1	0.3	0	8	0
SAMH substance abuse services in lookback year	0.1	0.4	0	15	0
Census county composition:					
Percent white	78.4	7.3	71	89	690
Percent black	12.2	4.6	5	17	690

	Distribution				
	Mean	Standard deviation	Minimum	Maximum	Number of missing
Percent Hispanic	18.0	7.9	9	26	690
Percent Asian	3.3	0.5	2	4	690
Percent American Indian/Alaska Native	0.4	0.1	0	0	690
Percent Native Hawaiian/Pacific Islander	0.1	0.0	0	0	690
Percent multiracial	2.8	0.4	2	3	690
Percent other	2.9	1.9	1	5	690
Average household size	2.5	0.2	2	3	690
Percentage of households with children	27.7	4.9	21	32	690
Percentage of high school graduates	88.4	1.1	88	90	690
Percent foreign born	13.2	2.7	9	16	690
Percentage of married households	44.37	3.73	40	51	690
Percent unemployed	8.90	0.37	8	9	690
Percent living under poverty line	15.57	1.39	14	17	690
Percent urban	96.19	3.28	90	100	690
Percent rural	3.81	3.28	0	10	690

Source: Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

[a]Other binary demographics, including race and gender, were included in the predictive model. The distribution of these variables can be found in VIII.2.

E.4. Florida binary predictors

	Number of children	Percentage of children	Number of missing
Placements			
Prior in-home placements in lookback year	1,492	18.0%	0
Prior out-of-home foster care placements in lookback year	128	1.5%	0
Average child welfare investigation risk level associated with the episode[a]			
Average risk level of 1	1	0.0%	0
Average risk level of 2	18	0.2%	0
Average risk level of 3	77	0.9%	0
Average risk level of 4	52	0.6%	0
Average risk level missing	7,955	96.0%	0
Missing investigation record	187	2.3%	0

Source: Florida OCW; Florida AHCA data; Florida SAMH.

[a]Child welfare investigations were classified as (1) low risk, (2) moderate risk, (3) high risk, (4) very high risk. Among those with missing investigation risk level information were children whose investigation preceding the t0 episode could not be identified (missing investigation record) and those whose investigation(s) preceding the t0 episode had missing risk level information. We classified these two groups of missing values into distinct categories.

B. Methods

Below, we describe the three phases of our analysis approach: (1) model development and validation (2) model assessment, and (3) interpretation.

1. Model development and validation

Model development includes the process of building ("training") one or more candidate predictive models, and choosing the one with the best predictive performance. Our procedure for model development consisted of several steps.

a. Split into training/test data

The goal of predictive modeling is to develop a model that makes good predictions on an external dataset. As discussed in Chapter VIII, to approximate this process, we created a "training" and "test" data set for both study sites. This is done by randomly splitting the sample into training and test data sets to be used for model development and model selection, respectively. Assigning a larger proportion of observations to the training set would result in better predictive performance, but it would also result in a less precise estimate of that performance on an external dataset (due to the smaller size of the test set). Given our total sample size and a relatively large number of candidate predictor variables, we created a 70/30 split—70 percent of the sample for both Tennessee and Florida was used to develop or train the models, while the remaining 30 percent was used to validate model results. This splits were chosen so that a similar proportion of superutilizers were present in both the training and test sets. Ultimately, how well the model performed on the test data set was of key interest.

b. Missing data strategy

Some variables in our data had missing values, for systematic reasons as well as reasons assumed to be random. In many cases, this missingness was informative—the fact that a child is missing this value could provide information as to whether or not the child will eventually experience superutilization. To account for this possibility, we employed a technique known as "missingness incorporated in attributes" (MIA) (Twala 2008). The approach, originally designed for decision trees, treats missing predictor values for an observation as a separate category, predicted differently than those for whom the predictor is observed. This technique avoids the need to impute those missing values, which is not appropriate when missingness may be informative. We employed MIA to handle the missing data for four types of variables:

- ***Geographic-level variables***. In both states, we were unable to assign a number of children to a geographic DCS region (for Tennessee) or county (for Florida), and thus could not match them with geographic-level predictors. This includes 1,652 children in Tennessee (13.7 percent) whose region was listed as "Child Abuse Hotline," "DCS Central Office," "SIU," or "Missing." For Florida, 690 children (8.3 percent) had an investigation associated with the t0 episode that occurred in a county other than Hillsborough, Pasco, or Pinellas (see Tables VIII.2 and VIII.4), but they were included as part of the study sample because they had at least one child welfare custody with an investigation county of intake in one of those counties. This missingness could be informative, as children who we cannot associate with a region or county may be more likely to change placements often, and thus have a higher likelihood of superutilization. MIA is a particularly attractive approach to account for the missing values in the geographic-level variables because they all follow the same missing data pattern (that is, if an observation is missing one of these geographic predictors, they are missing all of them). For children that could not be matched to a region or county, the contribution of all the geographic-level predictors towards their predicted outcome was captured by a single indicator corresponding to missing geographic-level data. On the other hand, for those who we are able to match to a region or county, the value of each of the geographic-level predictors was used to inform the prediction.

- ***Average child welfare risk level***. Because the average child welfare risk level could only take a small number of possible values, we treated this variable as a categorical predictor for each study site. Missingness could occur in two forms: either no investigation was associated with the t0 episode, or an investigation was identified but the risk level was missing. We split these two possibilities into separate categories of the predictor, allowing a child's predicted likelihood of superutilization to differ based on the type of missingness.
- ***Assessment data***. The assessment variables each had high degrees of missingness in both study sites, corresponding to unassessed children. MIA creates a "not assessed" category for these continuous predictors, allowing unassessed individuals to be predicted differently than those who were assessed.
- ***Hispanic ethnicity***. We treated Hispanic ethnicity as a categorical variable, with three levels: Hispanic, non-Hispanic, and missing.

Other than those discussed above, the only predictor in our dataset with any missing values was age, which was missing for a small number of individuals in each state. We considered these values to be missing at random, and imputed age based on other observed data using a powerful and flexible imputation algorithm known as multivariate imputation by chained equations (van Buuren and Groothuis-Oudshoorn 2011). Since only eight individuals (five in Tennessee, three in Florida) had missing age, we expect the effect of this imputation procedure to be minimal.

c. Candidate models

There are many potential algorithms for building a predictive model to classify individuals as experiencing superutilization or not. The most widely used and familiar approaches, simple logistic regression or linear probability models, are inappropriate for our data due to the large number of predictors we considered, with potentially high correlation between them. The predictors were also bound by a number of assumptions regarding their functional form, which we may not want to assume. We considered three prediction methods that vary by assumptions, flexibility, and interpretability, and are described below.

- ***Logistic regression with elastic net (EN) regularization***. The first model we examined was a logistic regression model. However, given the relatively large number of variables used for prediction, we decided to implement a penalized regression method known as an EN. The EN is designed to overcome the risk of over-fitting a model with many covariates while minimizing the risks due to collinearity between variables. The model does this by linearly combining what are referred to as the L1 and L2 penalties to find the optimal mix (Zou and Hastie 2005). The L1 penalty is associated with the least absolute shrinkage and selection operator (LASSO) while the L2 penalty is associated with ridge regression (Hoerl and Kennard 1988). Thus, the EN is essentially a logistic regression with an added constraint intended to maximize flexibility while not over-fitting the data. The EN is bound by many of the same constraints as logistic regression (for example, linear functional form in the logit and distributional assumptions). The model produces interpretable results (that is, familiar regression coefficients for each predictor) while also providing a more efficient framework for selecting relevant variables compared to stepwise methods. The potential downside is that the model is less flexible in its functional form, which can lower predictive strength.

- ***K-nearest neighbors (KNN)***. KNN (Altman 1992) is an approach in which the predicted outcome of an observation in the test set is based on the outcomes of the most similar observations in the training set (James et al. 2013). Similarity between two observations is defined by how close their predictors are to one another, summarized into a single index called the Minkowski distance. Once the most similar training observations ("nearest neighbors") are identified, their outcomes are combined as a weighted average (weighted by distance to the test observation) in order to generate a prediction. The KNN approach is a simple and often accurate method for classification; however, it comes at expense of the ability to interpret and rank individual variables based on their relative importance.
- ***Random forests (RF)***. Random forests are an extension of classification and regression trees (CART), in which predictions are made as a sequence of binary partitions, in a flowchart-like structure. CART models are well-suited as a prediction algorithm in cases with many predictors because they are robust to the inclusion of irrelevant variables and account for complex interactions between variables. However, they are known to be relatively unstable (high variability), and suffer from over-fitting, meaning they do not perform as well on external datasets. Random forests (Breiman, 2011) aim to address these concerns by "growing" many trees based on bootstrapped samples, and averaging the results (we grow forests of 500 trees). Additional robustness is incorporated by choosing random groups of predictor variables at each decision point in each tree. The result is a flexible modeling approach that often delivers predictive performance that is superior to more traditional approaches (such as OLS or logistic regression) due to the ability to account for complicated relationships with between predictors and the outcome. In fact, random forests are often considered to be a strong default prediction algorithm, due to their applicability to a wide variety of data structures (Hastie, et. al, 2001).

d. Tuning and model selection

Each model described above depends on one or more tuning parameters (components of the statistical model that can be modified to improve aspects of performance) that in turn affect model fit in the training set:

- EN: the degree of penalization (λ), and the balance between L1 and L2 penalties (α)
- KNN: the number of neighbors (k), and the Minkowski distance parameter (p)
- RF: the number of randomly selected predictors per split (m), and the minimum size of the terminal nodes of each tree in the forest (n)

To compare model performance in the training set, we selected the optimal tuning parameters using a 10-fold cross-validation within the training set. The 10-fold validation approach works by first randomly splitting the training sample into 10 evenly sized groups. One group is set aside and then the model is fit to the other 9 groups and is used to predict the outcome in the hold-out group. This process is repeated with each group serving as the hold-out group, until a prediction is made for the entire sample, and predictive performance can be assessed. To ensure that predictive performance is not dependent on the random split into 10 groups, we re-sorted 10 groups two times and averaged the results. The tuning parameters that resulted in the optimal predictive performance were selected and used for the final results we Our primary criteria for selecting the best tuning parameters is the AUC of the ROC curve (described in more detail below). To ensure that predictive performance is not dependent on the random split into 10 groups, we repeated the cross-validation twice and averaged the results. The tuning parameters that resulted in the optimal predictive performance (highest AUC) were selected and used for the final model for each model class.

Once the tuning parameters for each model were selected, we compared the cross-validated AUC statistics across the three model classes to choose the best-performing candidate model. This decision was made separately for the two states.

e. Measuring model performance

Model performance can be assessed by comparing the predicted probabilities of superutilization returned by each model to the true (observed) outcome (whether or not the child experienced superutilization during the predictive period). Our primary metric for assessing model performance is the AUC, which is a commonly used metric for comparing machine learning models (Hanley and McNeil 1983). AUC is a number between 0 and 1, with larger numbers reflecting models with better predictive performance. The ROC curve plots the sensitivity (true positive rate) on the y axis, and 1 – specificity (false positive rate) on the x axis, for every possible cutoff of the predicted probability. It also depicts the tradeoff between these two quantities for a given model. The ideal model would have high true positive rates and low false positive rates, which correspond to higher values of AUC. The AUC can also be interpreted as the probability that a randomly selected superutilizer will have a higher predicted probability than a randomly selected nonsuperutilizer. Generally, AUC statistics above 0.7 are considered to reflect a model that is at least moderately predictive of the outcome in social science research (Rice and Harris 2005).

Whereas AUC can be interpreted as a global measure of predictive performance of a model, we also examined how well the model identifies children experiencing superutilization (sensitivity) and nonsuperutilization (specificity). To do so, we needed criteria to determine which individuals the model is predicting to experience superutilization versus nonsuperutilization. Since our models return predicted probabilities of superutilization, this can be done by choosing a threshold (cut point) for the predicted probabilities above which we say the model is predicting the child to experience superutilization. As the cut point decreases, we identify more individuals as superutilizers. This increases the true positive rate, but also increases the false positive rate, thus raising sensitivity at the expense of specificity. A logical cut point would be a predicted probability of 0.5, but because superutilization with respect to placement moves is a relatively rare event (about 20 percent of the Tennessee sample and 15 percent of the Florida sample), predicted probabilities are generally low, and using this cut point results in very low sensitivity and high specificity. Instead, we chose the cut point along the ROC curve with minimal distance to the point of perfect prediction, which is 100 percent sensitivity and specificity (the upper-left corner of the ROC curve). We then calculated sensitivity and specificity based on this threshold, as well as the overall agreement rate, positive predicted value, and negative predicted value. The latter two quantities are the probabilities that someone predicted to experience superutilization (or nonsuperutilization, respectively) is truly a child who experiences superutilization (nonsuperutilization).

2. Model assessment and performance

After model development, we assessed the models based on predictive performance. The goal of the model assessment phase is to estimate how well our selected model would perform on an external dataset by applying the model, which was developed using the training sample, to the test sample. Predicted probabilities were calculated for each individual in the test sample and compared to the true (observed) superutilization status through an AUC statistic, as described above. The cut point (selected based on the training sample) was applied to the predicted probabilities from the test sample to further calculate sensitivity, specificity, agreement rate, positive predicted value, and negative predicted value. To obtain more robust estimates of these statistics, the entire model development procedure (model tuning, selection, and assessment) was repeated five times, each using a different split between training and test data, and the results over the five repetitions were averaged.

E.5 presents the results regarding the cross-validated model performance on the training data, which were used to select the final predictive model. For both Tennessee and Florida, the best-performing model was the RF model, with AUC values of 0.719 and 0.718, respectively.

E.5. Comparative Predictive Performance of three models using 10-fold cross-validated Results

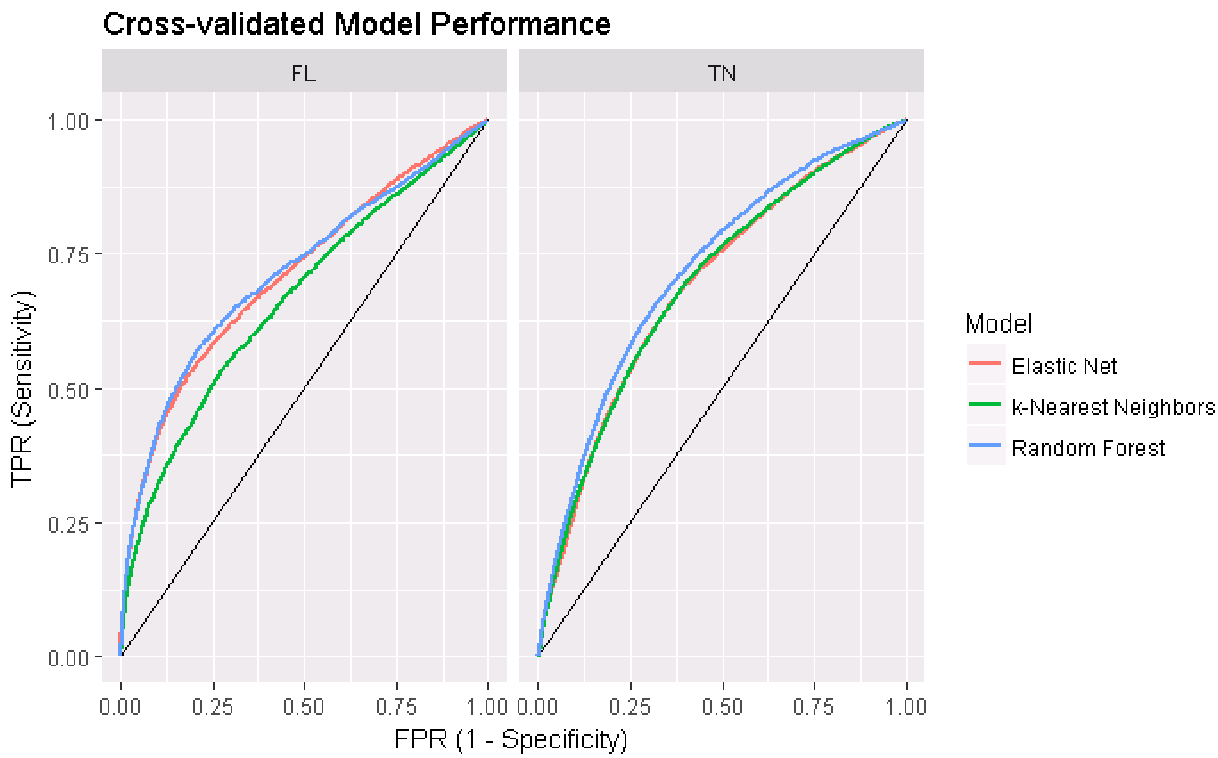
State	Model	AUC	Cut point	Accuracy	Sensitivity	Specificity	PPV	NPV
FL	EN	0.709	0.136	0.689	0.624	0.700	0.256	0.918
	KNN	0.646	0.132	0.648	0.552	0.663	0.214	0.900
	RF	0.718	0.046	0.739	0.583	0.765	0.291	0.917
TN	EN	0.686	0.190	0.636	0.660	0.630	0.310	0.881
	KNN	0.685	0.184	0.646	0.639	0.647	0.313	0.877
	RF	0.719	0.165	0.675	0.653	0.681	0.340	0.886

Source: Tennessee DCS; TennCare; Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

Note: **AUC** = area under the ROC curve; **Accuracy** = (prevalence)*sensitivity + (1-prevalence)*specificity; **Sensitivity** = the true positive rate of superutilization; **Specificity** = the true negative rate of nonsuperutilization; **PPV** = positive predictive value, or the probability that children classified as superutilizers truly are superutilizers; **NPV** = negative predictive value, or the probability that children classified as nonsuperutilizers are truly nonsuperutilizers.

The performance of each of the models may also be visualized as ROC curves (Figure E.1), where the RF model demonstrates slightly better performance than the EN and KNN approaches. Specifically, ROC Curves that are closer to the upper-left region of the graph are considered superior to those that are closer to the 45 degree line. The upper-left region of the graph represents the area in which sensitivity (the true positive rate) is maximized and 1 – specificity (the false positive rate) is minimized. An ideal model would exhibit 100 percent sensitivity and a false positive rate of 0 percent. The goal of the model is to come as close to this ideal point as possible. Figure E.1 illustrates that the RF model is closest to the upper-left region of the graph compared to the EN and KNN models.

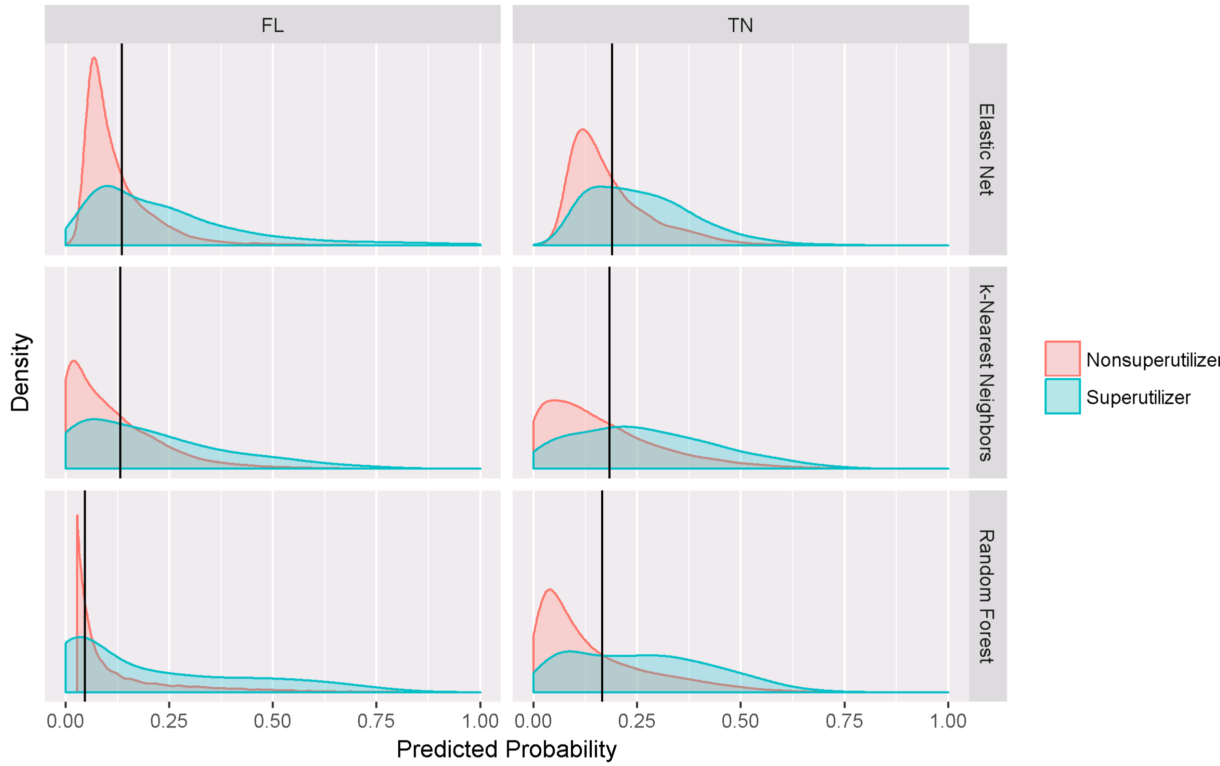
Figure E.1. Comparison of performance for the EN, KNN, and RF models based on ROC curves on cross-validated training set



Source: Tennessee DCS; TennCare; Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

Another way to visualize model performance is through the distributions of the predicted probabilities, separately by the observed outcome (Figure E.2). In this figure, the selected cut point for differentiating between children experiencing superutilization and nonsuperutilization is indicated by a vertical black line. As expected, the predicted probabilities are higher for those experiencing superutilization than those not experiencing superutilization for each model, but the ability to distinguish between the two differs by model. In Figure E.2 we can also visualize sensitivity (the proportion of the blue distribution to the right of the black line) and specificity (the proportion of the red distribution to the left of the black line).

Figure E.2. Distribution of the predicted probabilities of superutilization for the true superutilization and nonsuperutilization, for each study site and candidate model



Source: Tennessee DCS; TennCare; Florida OCW; Florida AHCA data; Florida SAMH; American Community Survey 2015; Census 2010.

3. Interpretation

The final phase of our predictive analysis is interpretation, during which we examine the relationship between predictor variables and the probability of superutilization to identify meaningful relationships. We do this in two ways—variable importance and partial dependence.

a. Variable importance

In conjunction with some of the machine learning techniques that we have employed, parsing out the importance of certain variables in the full model can be complicated. Nevertheless, we obtain a sense of their importance by considering how each variable contributes to overall model fit. In particular, for the RF models, we report a variable importance metric known as the mean decrease in Gini impurity for each predictor, which measures the contribution of the variable to the final prediction. More specifically, the Gini impurity is defined at each node of a decision tree, and measures how homogenous the outcomes are for the observations that pass through that node of the tree; lower values indicate a node with more homogenous outcomes. At any split in the tree, the Gini impurity before and after the split decreases, since a useful split will do a better job of differentiating between outcomes (superutilization vs. nonsuperutilization). Thus, a larger decrease in Gini impurity reflects a split that is better at separating children who experience superutilization from those who do not. Our variable importance metric, the mean decrease in Gini impurity for a predictor, was calculated by averaging the decrease in Gini impurity at every split in the forest that is based on that predictor (James et al. 2013).

b. Partial dependence

Although the variable importance metric from a RF can be used to identify the predictors that are most important in predicting the outcome, they do not provide much information on the shape of the relationship between these variables. To fill this gap, we present partial dependence plots for the top 10 most important predictors for each state (Hastie, et. al. 2001). Figures VIII.3 and VIII.5 depict the marginal probability of superutilization (or the regression-adjusted mean probability of superutilization) for fixed values of one particular predictor, averaged over the observed population.

For example, consider the partial dependence of superutilization on age, which we calculated at every age from 0 through 17. To perform this calculation, we took our observed dataset and replaced every child's age with the number zero. We calculated their predicted probability of superutilization (using the observed values of all other predictors), and averaged these probabilities over the entire dataset, to obtain the marginal probability of superutilization for zero year old children. We repeated this process for ages 1 through 17, and plotted the resulting values.

As age was identified as the most important predictor in both states, we also investigated whether the relationships between superutilization and the other top-10 predictors in each state were modified by age. This was done by calculating the bivariate partial dependence, that is, the marginal probability of superutilization for every combination of the variable in question and ages 0 through 17. We did not observe any strong evidence of effect modification by age, and therefore our discussion focuses on one-dimensional summaries of each of the top-10 predictors.

C. Programming

All programming was conducted using the `R` language for statistical computing, version 3.3.3 (R Core team 2017). The elastic net, k-nearest neighbors, and random forest algorithms were implemented using the packages randomForest (Liaw and Wiener 2002), kknn (Schliep and Hechenbichler, 2016), and glmnet (Friedman, et. al. 2011), respectively. Model training and tuning was implemented via the caret package (Kuhn et. al. 2017).

www.mathematica-mpr.com

Improving public well-being by conducting high quality, objective research and data collection

PRINCETON, NJ ■ ANN ARBOR, MI ■ CAMBRIDGE, MA ■ CHICAGO, IL ■ OAKLAND, CA ■ TUCSON, AZ ■ WASHINGTON, DC ■ WOODLAWN, MD

MATHEMATICA Policy Research

casey family programs