Chapter 1. State of the U.S. Foster Care System

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Suggested Citation: Wulczyn, Fred, MSW, Ph.D, *State of the U. S. Foster Care System,* in The Future of Foster Care: New Science on Old Problems by the Penn State Child Maltreatment Solutions Network (Sarah Font ed. & Yo Jackson ed., 2021). https://doi.org/10.26209/fostercare1

Abstract

In this chapter, I examine trends in the underlying utilization of foster care, drawing a connection between those changes and the fundamental problem of placement disparity. The narrative is organized around two themes. The first addresses the question of disparity. Much of what we have learned about disparity has come about from research that examines whether we find disparity when we look for differences in the experiences of Black, Hispanic, and White children and young people. Less attention, I argue, has been given to the question of variation in disparity rates. To highlight why this is an important question, given the interest in reducing if not eliminating disparity, I show how disparity varies using measures that capture disparity from a spatial and temporal perspective. I then ask whether supply induced demand for placement services influences placement utilization. Though the evidence is not per se conclusive, the inquiry does show how why it is important to study system effects as a distinct empirical problem. I close by calling for a foster care research agenda motivated by conceptualization rather than research method.

Introduction

The title of this chapter—State of the U.S. Foster Care System—hints at a paper of both breadth and depth. However, as even a casual observer surely understands, such ambitions are beyond the boundaries of a single chapter. In the U.S., the federal government grants states considerable latitude when it comes to state policy so long as policy fits within the federal framework. Even something as seemingly straightforward as the standard of proof needed to substantiate a claim of maltreatment differs dramatically between states, with some states requiring clear and convincing proof, others requiring a preponderance of evidence, and still others requiring credible, reasonable, or probable cause of abuse or neglect (Kahn et al., 2017; Provencher et al., 2014). Though there is a body of evidence that suggests the standard of proof used affects substantiation rates, there is no empirical research of which I am aware that extends that line of inquiry beyond substantiation and considers how the standard of proof affects time in foster care, placement stability, permanency rates, or reentry rates, even though child protective services serve as the front door to the foster care system. There is also the fact that nine states operate what are called county administered systems.[1] In those states, the county child welfare agency relates to the state child welfare agency in ways that mimic how states relate to the federal government. The state sets policy boundaries and counties, as the system administrator, exercise discretion within those boundaries. There are, as well, states that have created intermediate organizations to operate their foster care systems. Florida is a prominent example. Rather than a state-supervised, county-administered system, structurally and functionally, Florida operates a state-supervised, private agency-operated system in which private, non-governmental organizations (the Community Based Care organizations or CBCs) have been assigned functions that resemble county responsibilities in other states. Even in Florida, where some CBCs operate as administrative services organizations (i.e., they provide no direct services) and others look more like network model HMOs (Health Maintenance Organization), diversity of form is the key to understanding how foster care is organized in the U.S. In sum, there *is* a U. S. foster care system, but it is often best viewed from the bottom-up, with a clear understanding of how local variation adds up to the national profile, rather than the other way around.

With that said, I do think it is possible to both pose and answer questions that address themes with broad relevance. In doing so, I am not asking the reader to accept the evidence presented as illustrative of what's true locally. Rather, my goal is to promote local inquiry organized around a rather simple refrain: Is that true where I live? To that end, this chapter is organized around these questions:

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[1] Two states Wisconsin and Nevada operate hybrid systems. In Nevada, child welfare services in the rural counties are administered by the state, whereas the larger counties (Reno and Clark) operate their child welfare systems locally. In Wisconsin, Milwaukee county child welfare services are state administered; elsewhere the services are county administered and state supervised.

- Who uses foster care?
- What about disparity in the use of foster care?
- Should researchers, policymakers, and practitioners be worried about supply-induced demand?

In posing these questions, I want to broaden how we think about the evidence base used to guide child welfare policy and practice. The child welfare system is increasingly focused on the "what works" question that asks whether the services provided by child welfare agencies have their intended effect.[2] That interest has spawned a particular emphasis on evidence-based interventions and what we know from randomized clinical trials. The focus on evidence-based interventions is understandable. Resources are scarce and public investments should target services with known benefits. Having said that, it is important to note that evidence-based interventions answer the *what* question behind public policy: as a policymaker, what type of service investment I should make?[3] It is an important question but does not touch the *how much* or *where* questions that are equally important to the task of allocating resources. How much evidence-based service capacity (i.e., service slots for lack of a better term) should we buy, and where we should locate those services geographically given our desire to improve well-being at a public health level? Among other issues, what is important about these questions is that they are far less amenable to randomized clinical trials from an evidence development perspective (Nagin & Sampson, 2019). Put another way, the science of building effective service delivery *systems* requires more than the evidence derived from experiments. With a few simple examples, I hope to illustrate what that evidence looks like.

Who Is Placed in Foster Care?

In this section, I offer a simple overview of admissions to foster care between 2000 and 2018 with the aim of showing that foster care utilization has over the past 20 years shifted dramatically when viewed from a geographic and life course perspective. To do this, I start with the group of states with data for each of the following years: 2000, 2005, 2010, 2015, and 2018. From this collection of 15 states, I identified each child admitted to care for the first time for the listed years. In total, the evidence presented is based on the unduplicated records of 424,652 children.

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[2] See for example the Family First Prevention Services Act of 1918 (Family First Prevention Services Act, 2018). To secure federal funding for certain prevention services, states must invest in interventions that pass an evidence threshold.

[3] I use the word purchase here advisedly. Public policy and the fiscal decisions that flow from policy decisions lead services to be provided. In the case of preventive services, those services are often secured through the social sector. In that sense, the public agency purchases those services. The idea is that policy causes the service capacity to be built.

From this base, I group children into two categories: age at admission and county of placement. Age at admission is further organized into three groups: children who were less than 31 days of age at the time of placement, children who were 31 to 365 days old at the time of placement, and children older than 365 days at placement. I refer to these groups as newborns, infants, and older children and youth, respectively. The counties are categorized using the National Center for Health Statistics' urban/rural classification scheme (Ingram & Franco, 2014). That scheme groups counties into six categories: large central metro counties, large fringe metro counties, medium metro counties, small metro counties, micropolitan counties, and noncore counties.

Number of Admissions by Age

The total number of admissions by age and year is displayed in Table 1. Overall, comparing admissions in 2000 with those in 2018 shows a modest decline, from 83,091 to 82,586, a drop of just 505 children. Between those years, the number of admissions fluctuated. Over the 5 separate years shown in Table 1, the number of admissions reached a high point of 91,914 in 2005 and a low point in 2010 when there slightly fewer than 82,000 admissions.

In Table 1, the most important changes in admission patterns are tied to age at admission. Among children between the ages of 1 and 17 when admitted (older children & youth), admissions are down from 66,604 to 62,605. In contrast, the number of newborns and infants admitted increased relative to 2000. In 2000, there were 7,938 newborns admitted; in 2018, the number was 10,183. For infants, the change was less pronounced. Nevertheless, the number of infants (children between 31 and 365 days old) admitted in 2018 also exceeded the number admitted in 2000.

Table 1.

Number of First Admissions to Foster Care by Age and Year

	Year of Admission				
Age at Admission	2000	2005	2010	2015	2018
Total	83,091	91,914	81,818	85,243	82,586
Newborns	7,938	10,261	8,097	9,758	10,183
Infants	8,549	10,451	10,353	10,358	9,798
Older Children & Youth	66,604	71,202	63,368	65,127	62,605
Total	100%	100%	100%	100%	100%
Newborns	10%	11%	10%	11%	12%
Infants	10%	11%	13%	12%	12%
Older Children & Youth	80%	77%	77%	76%	76%

Admissions and Urbanicity

Along with the changes in the age structure of the population of children entering care between 2000 and 2018, there has been a significant shift away from the large central urban counties (see Table 2). In 2000, 50% of all children admitted to foster care for the first time came from the main urban counties in the state or what National Center for Health Statistics (NCHS) calls the large urban core counties. By 2018, those counties only accounted for 39% of all the admissions. On a percentage basis, the most significant increase was in the medium metro counties. In 2000, those counties accounted for 18% of the admissions; in 2018 the comparable figure was 22%. Though smaller, the proportionate share increased over the period from 2000 to 2018 in the remaining county types.

Table 2.

Number of First Admissions to Foster Care by Urbanicity and Year

	Year of Admission				
Urbanicity	2000	2005	2010	2015	2018
Total	83,091	91,914	81,818	85,243	82,586
Large Central	41,146	42,437	37,207	36,264	32,254
Large Fringe	12,644	14,280	13,132	14,224	13,832
Medium Metro	15,294	17,969	16,114	17,562	17,922
Small Metro	5,760	6,815	6,141	6,902	7,086
Micropolitan	4,912	6,115	5,532	6,035	6,728
Noncore	3,335	4,298	3,692	4,256	4,764
Total	100%	100%	100%	100%	100%
Large Central	50%	46%	45%	43%	39%
Large Fringe	15%	16%	16%	17%	17%
Medium Metro	18%	20%	20%	21%	22%
Small Metro	7%	7%	8%	8%	9%
Micropolitan	6%	7%	7%	7%	8%
Noncore	4%	5%	5%	5%	6%

Age and Urbanicity

The combined effects of changing demographics and the shift away from urban areas are displayed in Table 3. In the large central counties, admissions were lower in 2018 than in 2000. Among older children & youth, the change in admissions (-25%) was the most pronounced. In every other area, admissions were higher in 2018 than in 2000, with changes in admissions well in excess of 50% for some county groups. For example, in noncore counties, the number of children & youth increased by 31%, 66% for infants, and 210% for newborns.

Table 3.

Number of First Admissions to Foster Care by Age, Urbanicity, and Year

	Year of Admission					
Age and Urbanicity	2000	2005	2010	2015	2018	Change from 2000-2018
Newborns						
Large Central	4,584	5,144	3,926	4,438	4,212	-8%
Large Fringe	1,080	1,514	1,201	1,560	1,677	55%
Medium Metro	1,410	2,074	1,680	1,978	2,154	53%
Small Metro	420	713	607	793	874	108%
Micropolitan	287	529	468	660	780	172%
Noncore	157	287	215	329	486	210%
Infants						
Large Central	4,362	4,859	4,676	4,461	4,030	-8%
Large Fringe	1,292	1,579	1,659	1,763	1,619	25%
Medium Metro	1,554	2,066	2,014	2,124	2,016	30%
Small Metro	563	820	790	778	816	45%
Micropolitan	473	677	744	719	810	71%
Noncore	305	450	470	513	507	66%
Older Children & Youth						
Large Central	32,200	32,434	28,605	27,365	24,012	-25%
Large Fringe	10,272	11,187	10,272	10,901	10,536	3%
Medium Metro	12,330	13,829	12,420	13,460	13,752	12%
Small Metro	4,777	5,282	4,744	5,331	5,396	13%
Micropolitan	4,152	4,909	4,320	4,656	5,138	24%
Noncore	2,873	3,561	3,007	3,414	3,771	31%

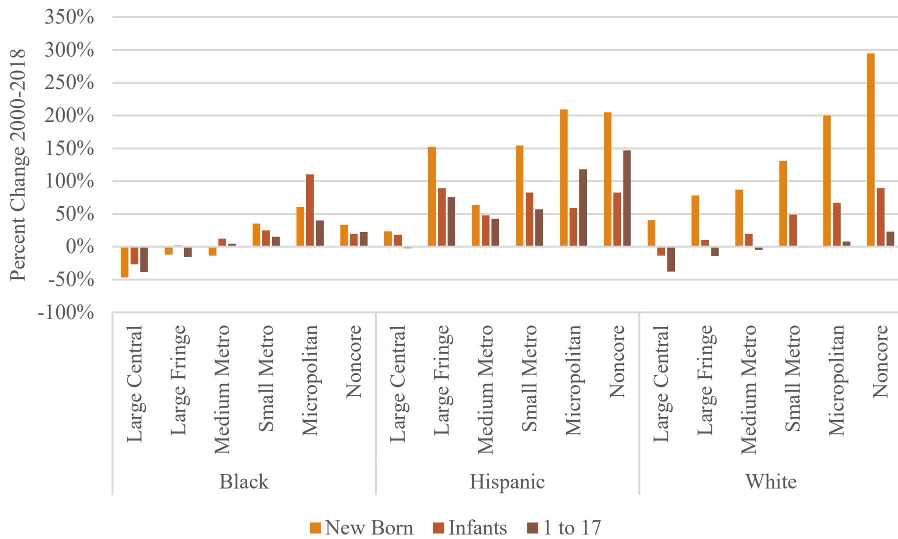
In the large fringe counties, the number of newborns admitted to care increased by 55%. Although small in number, admissions involving infants from micropolitan and noncore counties increased by more than 66%. In general, the admission increase was larger as one moves away from the large central urban counties. Within those areas, the largest increases involved the youngest children.

Of course, the shifting age composition and geographic distribution suggests that the racial and ethnic makeup of children entering foster care may also be changing. Figure 1 shows the extent to which this is true. Displayed is the percentage change in the number of children admitted to care for the first time in 2018 as compared to 2000 by age, race/ethnicity, and urbanicity. Generally, the changes described previously affected Black, Hispanic, and White children and youth similarly. For example, admission changes are more dramatic as one moves away from the large central urban core counties and toward the non-urban counties (i.e., the micropolitan and noncore counties). However, these changes are especially pronounced with regard to Hispanic and White newborns. Although small in number, the percentage increases were in excess of 150% for Hispanic newborns outside the urban core counties. Among Whites, the increase in newborn admissions was substantial (+200%) in the micropolitan and noncore counties.

For Blacks, admissions declined in the large central and large fringe counties and increased in other counties, with the largest increases affecting the very youngest children. For both Hispanics and Whites, the largest increase involved newborn children, regardless of the urban character of the county.

What do these trends mean? All-in-all, it is too soon to attach much meaning to what has happened without further analysis, which may strike some as a frustrating answer. Nevertheless, because we know that during this same period, rates of poverty in all parts of America have been on the rise but especially so in non-urban areas (Kneebone, 2017), it is premature to speculate too deeply without first understanding how trends in poverty correlate with trends in foster care. A preliminary review of the poverty data shows an increase in poverty in urban core counties but a decline in foster care placement. In the most rural parts of the country, foster care placement rates are up and so too are poverty rates. This presents a conundrum of sorts: in some places poverty is up but placement rates are down; in other places both poverty and placement are higher today than before. If poverty is somehow tied to the demand for foster care, then these data suggest that that relationship is more complicated than what we often hear: where you find more poverty, you will find the utilization of foster care is also higher. That observation begs the follow-up question, what is it about the places with growing poverty rates and falling placement utilization that differentiates them from other places? Are those differences important from policy, finance, and practice perspectives? Scott Allard (2017), among others, thinks the connection has to do with the service infrastructure available in places where both poverty and demand are growing.

Figure 1.
Percentage Change in the Number of Children Admitted to Care by Race/Ethnicity and Urbanicity: 2000 and 2018



Disparity and Foster Care

> "Knowing that a given inequality exists provides little information for those seeking to remedy it. Knowing the process that generates inequality, however, indicates possible points for policy intervention."
> (Knight & Winship, 2013)

The foregoing points to the deeper problem of disparity within the child welfare system generally and the foster care system specifically. The simple fact is the experience of Black children in foster care compared to children of other races and ethnicities stands apart. Because of what those differences say about how we as a nation support families, it is important to ask whether what we are doing now is aligned with what the science tells us is prudent from a public investment perspective.

I believe the answer to those difficult questions lies in what we can say about disparity, the way it varies over place and time, and what that variation says about the underlying causes of disparity. Surely bias, racism, and injustice are implicated but it is important to understand not only *whether* it is true but *how* it is true so that more targeted efforts are applied to problem both in terms of what has happened and, going forward, what is likely to happen (Reskin, 2003).

Toward that end, it is important to lay out what I mean when I ask about the ways in which disparity varies. By and large, based on the research that's been done, it is quite clear that what happens in the child welfare system to the families who encounter the system is correlated with race and ethnicity. There are two research summaries that provide an overview of what is known about disparity and child welfare (Fluke et al., 2011; Hill, 2006), so I will not repeat what those authors have already said except to say that at every point along the pathway through the child welfare system—maltreatment reporting, investigation, placement, and so on—it is extremely important to pay attention to how those experiences differ depending on whether the family is White, Black, Hispanic, Native American, Asian, or a child of some other ethnic, racial, or cultural group. It is only by asking and answering those diverse questions that is possible to say whether families are being treated equitably.

Strategically, there are two interrelated ways to approach the disparity question. The first asks whether there are differences based on race/ethnicity for a given outcome. Most research looks to answer this question: all things considered, is there a difference in the experiences of children connected to their race or ethnicity? For example, we might ask whether the likelihood of placement following a substantiated allegation of maltreatment differs for White as compared to Black children. If, after adding information about the family, the child, and whatever other attributes the researcher has at their disposal, the race effect persists, then we have substantial support for the claim that one group is having a different experience than another. To the extent we see differences that persist across various outcomes (e.g., reporting of abuse, placement, permanency), those differences become the foundation of what we know about disparity.

The second approach uses what we learn when we ask whether disparity is present to ask whether disparity is always the same no matter where one looks. It is this latter style of question I want to consider next. To illustrate this point, I consider both placement rate and length of stay disparities in one state. In doing, I only mean to illustrate the ways in which our understanding of disparity is dependent on how we choose to look at the issue.

In the first example, I note whether Black and White children enter care at different rates (rates per 1,000 children) at the state level. This is more broadly known as the statewide disparity rate. I add to that a substate view that asks whether the disparity rate as measured at the state level varies at the county level. To shine an even brighter light, I ask whether the size of the Black population living in the county is connected in any way to the level of disparity. I do so because I want to demonstrate that the observed level of disparity is a function of where one looks. Simply put, the statewide rate does not provide a necessarily accurate picture of disparity in places within the state.

The next question looks at how children leave care using a similar lens. The first question asks: at the state level, do Black children and youth leave foster care (i.e., adoption rates, reunification rates, etc.) in ways that differ from how White children and youth leave foster care (i.e., the exit rate disparity)? I follow that first question with a second: how is the state-wide disparity reflected in what happens at the county level?

To this second question, I add one additional twist. Most of the time, when researchers report on exit rate disparity, they will note that one group of children and youth leave foster care at a rate that is different than the rate reported for some other group (e.g., Black and White, male and female, urban and rural). Analytical strategies that fit this mold report the *average* effect of race on time spent in care. Though very useful its own right, the average effect does not address what might be interesting nuances. For example, given entry into care, what is the probability a White child and a Black child will leave custody within 6 months of entry? Is the level of disparity the same as the average or is observed disparity somehow more or less substantial? What about children who have been in care for more than 2 years?

It is important to both pose and answer these types of questions from a causal perspective because, in the early days of care, the bureaucratic processes that shape the experience of young people (i.e., the things caseworkers must do to provide high-quality, purposeful care) are very different than the bureaucratic processes that control cases that have been in the system longer given the elevated likelihood of adoption as time passes. For that reason alone, proposed solutions for racial disparities must pinpoint opportunities for change within the relevant bureaucratic process.

Entry Rate Disparities

Almost any conversation about race and ethnicity has to start at the population level. For essential context, it is important to know how many people we are taking about. In the state discussed in this section, at the time, 22% of all children living in the state were Black, whereas 28% of foster children were Black.[4] The disparity rate tied to the over-representation of Blacks relative to Whites is manifest in entry rate differences. The Black child admission rate was 3.78 placements per 1,000 thousand children as compared to 2.99 placements per 1,000 White children, which is a difference in the admission rate of 1.27.

Because the state's child population, when divided by race, is concentrated in different parts of the state, it is important to ask whether the disparity rates in counties separated into groups based on the size of the Black child population would reveal potentially important differences. To illustrate the point, I organized counties into three groups: counties where I thought of the population as small on a percentage basis, counties that occupied the middle ground given the overall distribution in the state; and a third group of counties with the largest populations.[5] There were 24 counties out of 95 that fit into this last group—the counties with the largest Black child populations on a percentage basis. Of those 24 counties, four accounted for about 70% of the Black children living in the state. Put another way, 70% of the Black children live in just four counties. When we use a statewide average to describe disparity, we are glossing over the reality that children are exposed to the system that operates where they live. Other children, children who live elsewhere, are exposed to a similar but different system. Breaking

[4] For the observations I am making their level of generality it is not important to know that state.

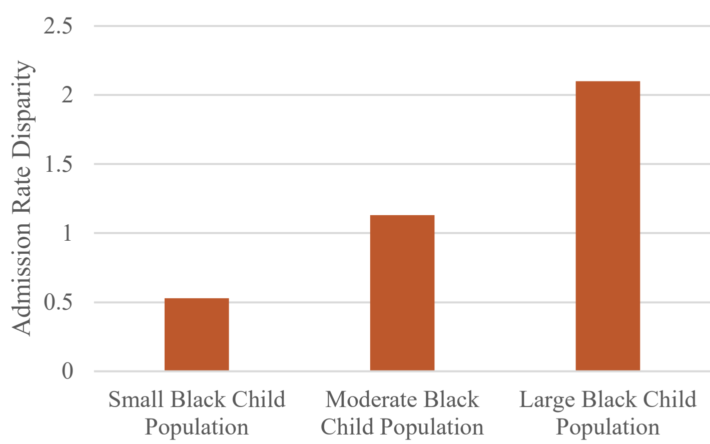
[5] I have not reported the thresholds used to categorize the counties because I want to focus the conversation on the concept of the average and its applicability to lower levels of geography. The point is this: even an arbitrary classification of counties reveals substantial variation around the average. What does this mean? The answer to that question requires more careful thought and some understanding of the cutoffs. Here, the question is much easier. If I divide counties into three groups organized around small, medium, or large in size, will a single disparity rate emerge, one that describes small, medium, and large counties, or do large counties where most Blacks live have a disparity rate that differs from the state disparity rate?

disparity rate calculations into smaller parts, to understand what is behind the average, more readily reveals the importance of context where many of the structural causes of disparity likely reside.

The findings highlight the reasons why this is an important point (see Figure 2). In the counties with small Black child populations, White children were more likely to go into foster care than Black children, not less likely. In counties with a Black child population of moderate size, there was near parity, with a slightly higher risk among Blacks. Only in the counties with large Black child population was the entry rate for Black children substantially higher than the entry rate for Whites. In those counties, the rate of entry for Black children were twice the rate of those for Whites. That figure is, of course, substantially higher than the statewide average. To the extent the modest statewide rate would have led someone to conclude that the issue of disparity is somehow less troublesome than in a state with a disparity rate that is substantially higher, then an important opportunity to act would have been missed.

Figure 2.

Admission Rate Disparities by Population Size as Proportion of Total Child Population



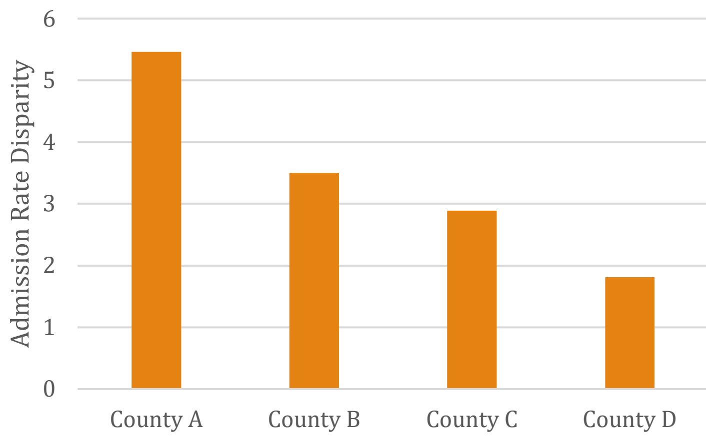
It also important to bear in mind that, even in the counties that contribute to higher-than-average disparity rates in the so-called large counties, there is nevertheless substantial variation between the counties that belong to the larger cluster. Figure 3 illustrates this point. Here, I am showing the disparity rates for the five largest counties in the cluster of counties with the largest populations of Black children. From this view, it is quite clear that, even in a cluster of counties with higher-than-average disparity rates, the contributing counties themselves have rates of disparity that are substantially different from one another. Specifically, county A has a disparity rate of 5.5 as compared to county D, where the disparity rate is 1.8. The disparity in the disparity rates is 3.05 (5.5/1.8), which is larger than the statewide disparity rate.

To put it most simply, the one overall statewide disparity rate is made up many disparity rates measured at the county-level. With these simple data, I cannot say why that is the case and it is certainly possible that these differences are not substantively meaningful.

Whether the differences are substantively meaningful is an empirical question. Given the issues in play, it is important that that work be done.

Figure 3.

Admission Rate Disparities in the Four Counties With the Largest Black Child Populations



Exit Rate Disparities

Over-representation of one group relative to another happens because there are differences in the rate of entry and differences in the probability of exit. I have already covered the entry dynamic (albeit in very modest detail). My attention now turns to children leaving care and whether disparity is a function of placement duration. Specifically, I want to know whether disparity measured as the likelihood of leaving placement to permanency within the first months of placement is substantially different than it is at other times during the placement process.

Figure 4 below highlights the basic point. For the figure, I calculated the conditional probability of achieving permanency based on how long a young person has been in care. I did this by dividing the time spent in care into discrete intervals of time, 6 months in this case. At the start of each interval, I ask who is in care at the beginning of the interval and who leaves during the interval. At the start of each interval, the only people still in care are the young people who have yet to leave. I refer to this as the period-specific likelihood of permanency.

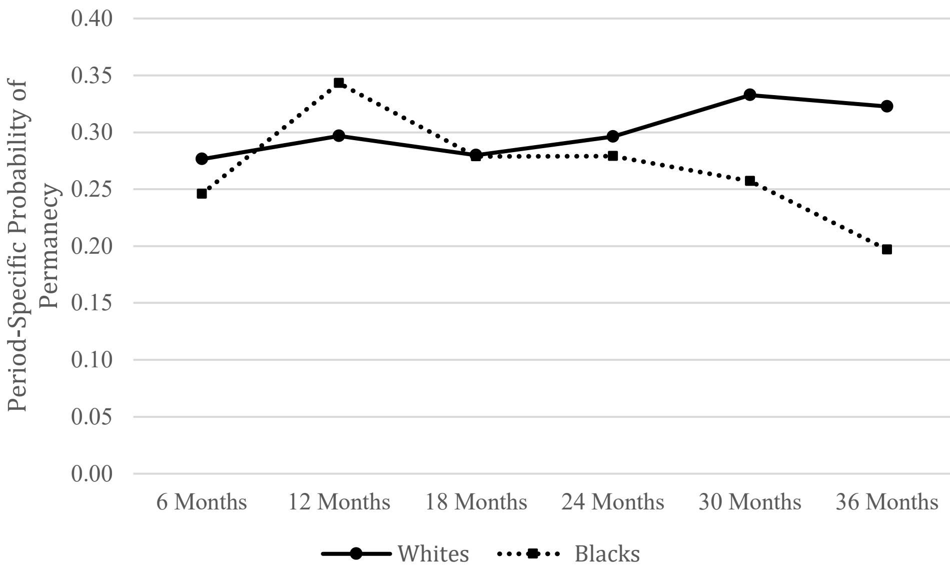
Before delving into what Figure 4 shows, it is important to set the context using statewide data. Although not shown specifically, when state-level exit probabilities for Black children and White children are compared, the difference (i.e., the average effect) is not statistically meaningful. *Black children are as likely to leave care as White children* are. This finding is itself interesting in the national context. However, as before, when we look deeper, we see the sort of nuances we should be considering when thinking about the mechanisms that give rise to disparity. Specifically, within 6 months of admission to foster care, Black children are less likely to achieve permanency, but only slightly so. In the second 6 months, when the Black children still in care are compared with the White children still in care, Black children are actually more likely to achieve permanency than White children. Among children still in care at the start of the third and fourth person-periods (children in care for at least 1 year), there are negligible reunification differences. That is, there is no disparity in exit rates among children in the specific group—children in care for at least one year. Thereafter (2 years and onward), disparity grows through person-periods 5 and 6, such that we see two distinct exit processes: early on, the Black/White disparity is negligible and only in the third year do sharp differences emerge.[6]

Of course, this is but one state. These patterns may describe what is true in some states but not others. Or we might find patterns in those other states that are altogether different. Either way, the field is left with a fundamental question in need of an answer: what else goes along with these differences and how should that evidence weigh on the decisions that must be made to *solve* the injustices embedded in our social institutions?

[6] The analysis here is focused on permanency rate disparities. Of course, one would want to know more about reunification disparities, guardianship disparities, and adoption disparities. Those data were analyzed and are covered in a report that can be found here: (Wulczyn et al., 2019)

Figure 4.

Period-Specific Probability of Permanency by Race



Supply-Induced Demand

I am going to continue with this theme—variation in fundamental measures of disparate treatment—but shift the focus and consider whether Black youth are more likely than White youth to be placed in congregate care, a form of disparity that is rarely studied. Following the rationale already laid out, my questions have three related dimensions: (1) is there disparity in the use of congregate care?; (2) does the disparity vary from place to place?; and (3) regarding the places where disparity tends to run above average, is there anything else about those places worthy of further consideration empirically? For answers to that last question, I take a systems view with an emphasis on resource constraints (Sugihara et al., 2012; Wulczyn & Halloran, 2017). Everyone knows that systems operate under conditions of resource constraints—money, people's time—but social scientists working on child welfare problems have not done much to show how resources constraints affect children and families directly. I want to demonstrate one such pathway with what follows and then tie that pathway back to disparity. I do not have the space to make all the connections, but there is an emergent narrative that is important to consider.

The discussion hinges on the notion of supply-induced demand. In health care, the formal term is supply-induced demand elasticity (Gooch & Kahn, 2014), which alludes to a connection between the supply of services and the utilization of those services. For example, if beds are in short supply, the threshold of who gets a service becomes a judgment that must be made. It is possible under those constraints that some who needs a service will not get it, as we have seen with COVID-19 and ICU beds. There is, however, evidence that suggests the opposite is also true, even in the case of ICU beds (Delamater et al., 2013; Gooch & Kahn, 2014; Roemer, 1961). At times when there is an over-supply of a service relative to demand, the over-supply of beds influences who gets the service because the net tends to widen, especially if services provided are reimbursed on a fee-for-service basis (as most congregate care in this country is). Supply-induced demand reinforces a dynamic that affects both the mix of cases served and the outcomes of those served (Rice & Labelle, 1989; Stelfox et al., 2012; Valley & Noritomi, 2020).

To see the connection more clearly, it is important to see congregate care, especially under fee-for-service conditions, as a system that tends toward bed utilization levels that yield the revenue needed to keep the organization operating, an outcome that is, under the current business model, in everyone's interest. Public agencies rely on stable providers able to sustain the service quality standards set by the public agency; financial stability allows providers to retain the staff they need to support program quality commensurate with the expectations of their public agency partners. Nevertheless, when revenue is tied to bed utilization, it is easy to see why, under these conditions, utilization tends toward targets that promote organizational stability.

If we characterize bed capacity as the number of beds in the system at any given time and utilization as the number of those beds occupied by a young person, we see that utilization is a simple function of admissions and discharges. When a young person is admitted, utilization rises closer to the limit of capacity; when a young person is discharged, then utilization falls relative to capacity. On balance, utilization is maintained through a balance of admissions and discharges, at least theoretically. More importantly, if utilization of bed capacity is set with a target in mind (the target being the utilization needed to realize a certain level of revenue), then one should expect to find a link between admissions and discharges such that, as young people are discharged, beds open and admissions rise.

To test whether such an assertion is true—that admissions and discharges in the congregate care system are linked—my colleague John Halloran and I borrowed methods from the biological sciences (Wulczyn & Halloran, 2017). In population biology or population ecology, scientists have been grappling with the problem of population growth and decline relative to resource constraints for quite a few years (Goel et al., 1971; Takeuchi, 1996). Although that science is more complicated than I have room for here, I will draw the straightest line between the problem of congregate care utilization and population biology that I can.

Fundamentally, we analogize admissions to and exits from foster care as the birth/death processes found in classical population models. Drawing from population theory, we then argue that if foster care is a resource constrained system similar to a biological eco-system, then the behavior of the population over time should provide evidence of carrying capacity and feedback mechanisms that represent adaptive behavior within the system. That adaptive behavior is observed through changes in admissions and discharges that operate in unison with each other. In short, if demand (i.e., admissions) for congregate care is tied to the supply of beds, then we should see admission and discharges move together, as one balances off the other to achieve utilization targets (Fama & French, 2000; May, 1974; Nielsen & Hannan, 1977; Sugihara et al., 2012; Tuma & Hannan, 1984; Wulczyn, 1996).

The details of how we went about searching for evidence of supply-induced demand can be found in our paper (Wulczyn & Halloran, 2017). As a summary, I will point to where we started the analysis. We constructed weekly counts of how many children were admitted to congregate care and how many were discharged. We used data going back 15 years at the state level and compiled the data for 728 weeks of continuous time series data.

With that data, we needed to answer two fundamental questions. First, do the time series data for admissions and discharges exhibit structure, or is the time series random? That is, what do we see when we look at admissions from week to week and discharges from week to week? If those individual time series data are random—the change from one week to the next has no rhyme or reason—then the likelihood we will find structures within the data related to the resource constraint (i.e., beds) is unlikely if not impossible. The second question requires a more direct assessment of admissions and discharges. Although we go into much more detail in the paper as to how we went about answering the second question, especially with regard to the references, here I will simply report the correlation coefficient to answer the relatively simple question: are admissions and discharges correlated? We regard this as preliminary evidence that a resource constraint exists. In the paper, we strengthen that conclusion with additional evidence using the methods adopted by population ecologists.

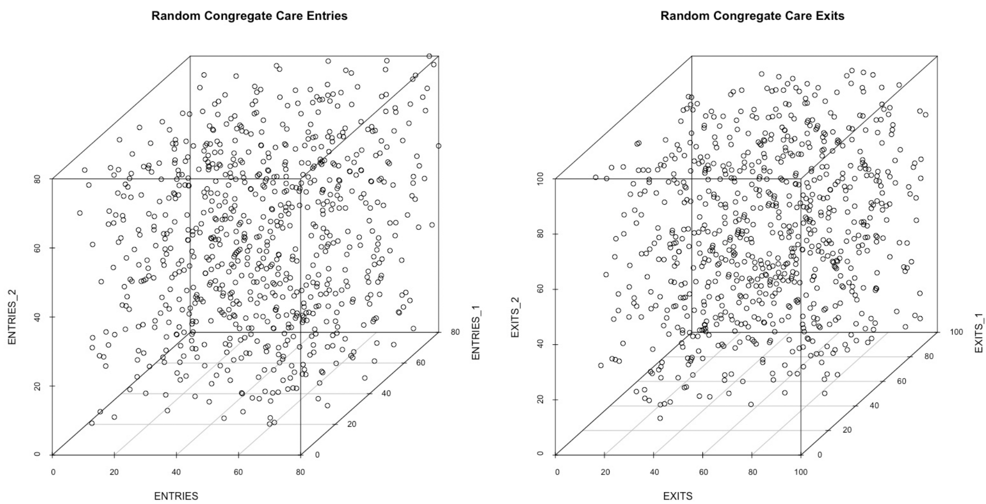
Suffice it to say that when admissions and discharges are viewed on a weekly basis, the resulting time series is rather jagged. To the naked eye, there are patterns there, but the overwhelming visual impression is disarray. It *appears* that the number of admissions is as likely to go up one week to the next as it to go down. In two dimensions, any structure that is there is difficult to see.

Another way to examine structure within the times series is to project the data into what is called three-dimensional state space. If the time series is random, it will seemingly fill the space evenly; more structured data will form a cloud with structure. To illustrate the distinction between a random time series and time series data with structure, I will start with three-dimensional time series plots using random data for a single state taken directly from the paper.

The random data are generated from a time series data for admissions and discharges taken from the actual weekly count of admissions and discharges. In other words, we reshuffled the points into a random order. As displayed, the points represent the number of admissions (or discharges) to congregate care at time = 0, (x), time = $t - 1$, (y), and time = $t - 2$, (z) with the time points lagged from each other by a certain number of weeks, which in this case was 1. The results are in Figure 5.

Figure 5.

Three-dimensional lag plot of the variable of interest (x-axis) compared to the variable position in the first-order lag (y-axis) and second-order lag (z-axis). In the entries plot (a) and the exits plot (b) the data is randomly generated using the observed parametric bounds of the time series.



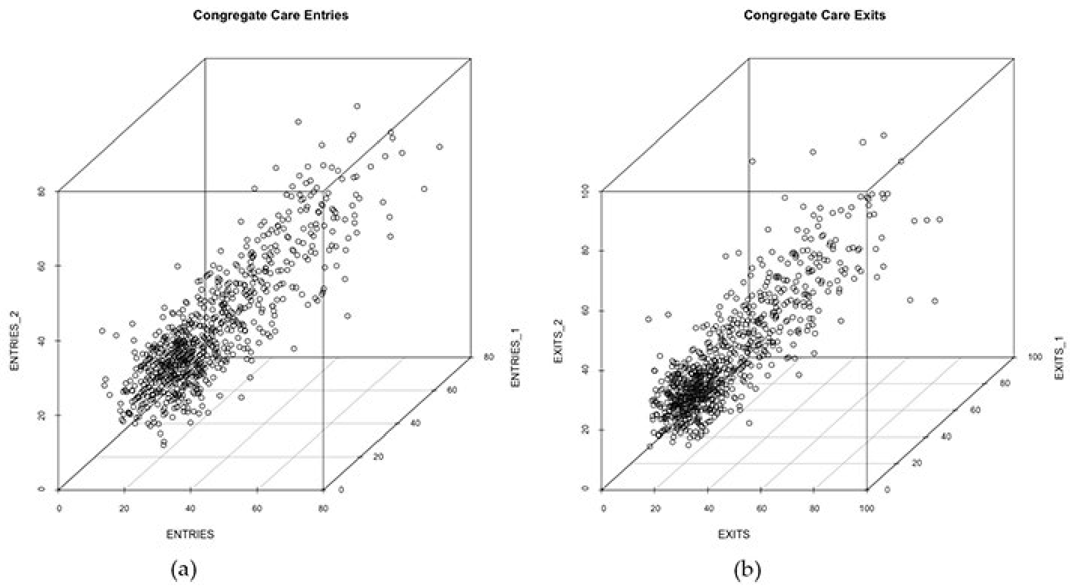
(a) (b)

As expected, the random plot shows no structure, which means that the next value for admissions in the time series is as likely as any other value, provided it falls within the range of values ever produced. The same is true for the discharges. Among other things, the random time series means that there is no apparent force within the system compelling the number of admissions or discharges in some direction: the number of admissions and discharges from one week to the next is random.

In Figure 6, we show three-dimensional scatter plots for the observed admissions and discharges to congregate care in their actual temporal order (i.e., as they happened). The admission and discharge counts are displayed as before, along the x-, y-, and z-axes with a lag of 1 week. As hypothesized, the data for the congregate care series are more tightly patterned than the random time series. This means that the next point is more likely to fall within a specific region of the three-dimensional space. The non-random nature of the plot is, we believe, a marker for structures that have explanatory power pertaining to the system that generates the time series data. One such structure is the proposed relationship between admissions, discharges, utilization, and revenue targets.

Figure 6.

Three-dimensional lag plot of the observed entries (a) and exits (b) to congregate care, 2000 to 2015, in their state at time zero (x-axis) compared to the variable position in the first-order lag (y-axis) and second-order lag (z-axis).



Regarding the correlation coefficient, using the same data used to generate Figure 6 we found that admissions were correlated with discharges at a .6898 level. If that's translated into explained variance, the r-square suggests that about 47.5% of the variance in discharges is explained by the variance in admissions. On a theoretical level, although there are other reasons why admissions and discharges go up and down over time, I do not see a more powerful predictor of admissions and discharges than discharges and admissions, depending how one thinks about the causal arrow. In either case, the data strongly suggests that at the system level there are bed constraints that act on who is admitted into congregate care. It is best to think of this constraint as a range rather than a point estimate. That is, utilization over time will move between an upper and lower bound. As utilization approaches the upper bound, access goes down; when utilization moves downward, access goes up. It is important that we know how these constraints work in the context of case-level decision making. In health care, as I said, they have labeled this dynamic as supply-induced demand elasticity. The evidence in that context is rather strong. I think there are reasons to further explore how resources constraints affect what happens and to whom in the child welfare system. We tend to see case-level decisions as based on the merits of the individual case. This notion of supply-induced demand elasticity, because it flies in the face of that conventional thinking, ought to be studied more carefully.

What does this have to do with disparity? I start with assumption that supply-induced demand is more common in some parts of states than others. For convenience, using counties as a unit of analysis (rather than states), I asked whether the admission/discharge patterns observed at the county level are similar to each other: is supply-induced demand uniform or is there variability in how strong the supply effect is? To get an answer to that question, John Halloran replicated the calculations in our paper using admission and discharge data for 1,271 counties. We found that the supply-demand dynamic is a complicated one. In some counties, admissions and discharges are very close to zero, which means that there is no meaningful connection between supply and demand. In urban counties, the signal that corresponds to the supply effect on demand tends to be much stronger although the signal is often detected in smaller counties between the rural and urban extremes.

To make what we found more useable, we divided the counties into three groups: counties with a statistically distinct signal, counties with a signal that did not cross the threshold of statistical significance, and counties with no real signal at all. We then asked whether disparities in the use of congregate care were connected in any way to supply's effect on demand.

More work is needed before we fully understand the causal mechanisms at work, but the initial results are interesting if not provocative: disparity and supply-induced demand are probably linked. To see the pathway, we started with simple unadjusted odds ratios showing that Black youth were more likely to be placed in congregate care than either White or Hispanic youth (50%, 44.5%, and 39.6%, respectively). In keeping with how we talked about the average disparity ratios, these differences reflect what's true without regard to state or county boundaries.

The next step involved linking our measure of supply-induced demand to disparity. Using counties grouped according to the measured effect of supply on demand, we computed the average disparity ratio for each group of counties after considering the mix of cases served in each county. From those results, we observed higher rates of placement among older youth and males, regardless of race and ethnicity. Rates of congregate care placement were also much higher in counties where the supply signal was strong as compared to weak even after controlling for child-level factors linked to utilization. To some extent, urbanicity was implicated in whether a young person would be placed into congregate care, but the urban effect was undone by the supply effect. That is, the thing about urban areas that the contributes higher congregate care utilization is tied to the supply effect. Urban areas and the supply of congregate care are likely correlated, but in non-urban areas (e.g., suburban counties), the supply effect is likewise observable. Taken together, the supply effect seems more important than the simple notion of urbanicity.

For the last step in the analysis, we asked whether the supply effect altered the Black/White and Hispanic/White disparity ratios. It is an interesting question because of how the populations of White, Black, and Hispanic foster children are distributed among the counties. Put simply, in the counties where the supply signal is weak, 70% of the children entering care

are White. In the counties where the signal is strong, two-thirds of the children are either Black or Hispanic. That means, to the extent supply affects demand, Black and Hispanic children face greater exposure to those systemic conditions than White children do. With regard to disparity, the question shifts: what is the placement rate for White youth in counties with a strong supply effect, and what is the placement rate for Black and Hispanic youth in counties with a weak supply effect? These are the contributing streams of influence that give rise to what we see at a multi-state level.

To summarize what we found, it is probably easiest to work from the highest level downward and then draw some simple inferences. Before going down that road, I want to add one additional variable to the model. Supply effects are not the only source of macro or institutional influence within child welfare systems. States differ with regard to how they regulate the congregate care industry. In fact, the ways in which states differ from a regulatory perspective, as noted at the outset, is itself highly variable. By extension, we can and should expect that policy differences exert a causal influence such that what we observe in a state with a given policy is different than what we observe in a state without that policy.

To make sense of the policy morass, we looked for policies in the states that sought to control access to congregate care through the use of an assessment. From that data, we created a binary variable: the state (and the counties in the state) was assigned one if we found statutory language that crossed our threshold and zero if no such language could be found. Then, the risk of being placed in congregate care was assessed at the county level alongside information about the young person (e.g., their age) and other features of the county including the strength of the supply signal.

Viewed through that particular lens—how much does context influence the level of disparity we observe—the findings are substantial. The unadjusted disparity rate for Blacks relative to Whites was 1.43; for Hispanics, the unadjusted disparity rate was .69. With proper statistical controls for county size and other county attributes (the policy and supply effects), unmeasured state and county characteristics, and characteristics of the child included in the model, the lowest Black/White disparity rates were found in counties where we found supply effects along *with* a policy preference for conducting assessments. The same could be said for the Hispanics with one exception. Hispanics are generally less likely to use congregate care, and the biggest differences relative to Whites are in counties with both a supply and a policy effect.

I should also point out that in counties without a supply effect and no expressed policy preference for assessments, disparity was much higher, but not because the risk of using congregate care is much higher in those places. Rather, counties where there is no real supply signal have low placement rates. The actual disparity arises from these low base rates so it is important to remember that low base rates for Whites and Blacks are sometimes if not always associated with considerable disparity. The reverse is also true: counties that use a lot of congregate care may have low disparity, relatively speaking. Those differences, I would argue, should weigh on how experts approach the solution phase of the problem-solving process.

Although there is more here worth exploring, I return now to a theme raised earlier in the chapter when I mentioned there are two ways to study disparity. In the first, Black/White differences are the independent variable in the model used to explain the variation in outcomes. Question of this sort answer the question: do we find disparity when we look for it? The second type of question moves the Black/White differences to the dependent variable side of the model and asks, more directly, what causes disparity. Too often the answers to the first question are taken as an answer to the second. I have tried to show here how analysis that considers both questions yields a more fruitful line of inquiry. On the one hand, we know that there is disparity; on the other, we know that the measured level of disparity stands out in some places more than it does in others. From a structural perspective, we linked supply/demand dynamics to the level of disparity, a path that is tied to an important feature of the underlying system: how the system is funded exerts a casual influence on what happens to children. If we hope to reduce disparities, a specific proposal to undo the structural mechanisms linked to how the system is financed would be a step in the right direction.

Foster Care and the Science of Investment

The collection of organizations interested in improving the nation's foster care system is a large one. There are, nevertheless, core problems that persist despite the efforts of that assembly to make improvements. To say the persistence of those problems is a source of political frustration is no doubt an understatement. For sure there has been progress, but work remains.

To start, because child protection systems operate at an institutional level, one does need a comprehensive, active understanding of where the demand for child protection services is greatest, how the demand is changing, and why. To the extent these explorations help us understand the causal mechanisms underlying why some families struggle, we have to think about what these observations tell us about the prospects of policy and practice changes.

These broader types of questions—questions motivated by, among other things, a clear conceptualization of context and its influence on families and child protection outcomes—are increasingly important to the science behind the evidence-base policy makers need to make smarter decisions. Starting with the changing face of foster care, I will simply note that the demand for foster care—measured as the rate of placement—is growing in non-urban areas. In terms of investing in better outcomes, we have to ask ourselves whether the service infrastructure in areas of growth exists in sufficient, cost-effective quantities to slow the demand for foster care in those places. Among others, Scott Allard thinks the social services infrastructure found in suburban and rural areas of America lags behind the geographic redistribution of vulnerable populations, an insight with profound implications for how we carry out social welfare investments and with what benefit (Allard, 2017).

With regard to disparity, we have to acknowledge that the form disparity takes, even in the case of injustice and bias, is likely more nuanced than we often consider. In one state, we found places in that state where White children and youth were more likely to be placed than

Black children and youth. Even in the places where the majority of Black children live, admission rate disparities varied considerably. This is one state. What about the others? Are there generalizations we might make from that sort of comparative research? Investments in the solutions that address disparity have to take these systematic, contextually grounded differences into account lest we risk investing in ways that undermine our good intentions.

Last, we found evidence of system effects (Forrester, 1971; Jervis, 1998) that speak to how the organization of services affects the interventions. Put simply, if we fail to consider system structure (e.g., the mechanism of finance) in our efforts to reform the system, we will likely find ourselves continually frustrated by a system that is resilient to our efforts to induce change, as many systems are (Forrester, 1971). If we fail to recognize the role of structure, both theoretically and empirically, our investments in systems change will result in lower returns.

The theme that runs through these examples ties back to whether randomized experiments are the gold-standard way to know what we need to know about the workings of the complex, whole-of-government systems we have built to lift up the well-being of children. None of the empirical examples discussed here were derived from randomized experiments, yet the evidence provided reveals a system in the midst of changes that surely shape how we should think about devising an approach to child protection and foster care that is both more effective and efficient.

Conclusion

Setting aside the politicization of social policy in the U.S. and elsewhere, we do not need a new science of foster care as much as we need greater diversity in the science we apply to problems building a better foster care system. We have witnessed a growing commitment to the evidence-base in child welfare, and the shift is laudable. However, if the emphasis remains centered around interventions that work, we are likely to encounter disappointment, for the evidence of what works represents only a portion of the evidence we need to operate a more effective and efficient foster care system (Deaton & Cartwright, 2018; Nagin & Sampson, 2019). A broadened view of the foster care system as a system that affects the lives of children is what we need. For that, a research agenda motivated by conceptualization rather than research method is essential.

Acknowledgments

I would like to acknowledge the state child welfare directors who have supported the Center for State Child Welfare Data for the past 17 years. Without their support, the work of the Center would not be possible. I also want to thank all of my colleagues at the State Data Center. It is an extraordinary group of individuals whose commitment to finding a better way to serve young people and their families is always inspiring.

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