THE UNIVERSITY OF CHICAGO

POPULATION DYNAMICS IN THE CHILD WELFARE SYSTEM

A DISSERTATION SUBMITTED TO

THE FACULTY OF THE SCHOOL OF SOCIAL SERVICE ADMINISTRATION

IN CANDIDACY FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

BY

JOHN THOMAS HALLORAN

CHICAGO, ILLINOIS

AUGUST 2018

This dissertation is dedicated to
my child clients in Vermilion County, Illinois, 2006–2010

Table of Contents

List of Figures

List of Tables

Acknowledgements

The focus of this dissertation is on the flow of time and the impact of that flow on the movements of certain outcomes. Though I avoided (or, more accurately, was led away from) citing Heraclitus in the main body of this text, I will indulge now with two quotes. The first from Fragment 50:

> I myself am saying this: it is my *logos*. But in hearing me speak, listen not to the Heraclitus who is talking but to *the* Speaker whose Saying I am uttering, having heard and heeded him—as should you. Then you too will say, along with me and 'him'—for I am telling of a power that addresses us—that there is Something Wise, which it is wise for us to say along with the Logos and in agreement with it, because it is found embodied in our world: There is a Unity relating Everything and All Things.[1]

The second, is from Fragment 12: "A river—it is not possible to step in the same one twice. For other and ever other water flows on." These Heraclitian concepts of relational unity in the midst of constantly changing flow have provided me with a great deal of conceptual energy over the course of this project. It is a small irony that the study of flow must result in some moment of concrete existence, when, in fact, this dissertation is simply one moment in many leading up to and hopefully continuing well beyond the date of its submission. Freezing the moment, though, does provide an opportunity to pause and give thanks for the privilege of being allowed to sit back and wonder at the flow of the world.

Firstly, I would like to thank, with greatest love, my family for their support and patience. Monica, Nora, and Clare are my logos. My unity. My wife, Monica, was the major driver of my leaving the practice of law and deciding to attend the University of Chicago. She understood,

[1] Quoting Eva Brann's "meaning-expression" of Heraclitus's Fragment 50, which is usually translated as "listening not to me but the Logos, it is wise to acknowledge that all things are one" (Brann, 2011, p.18).

almost immediately, the depth of feeling that I have for children involved in the legal system, and has encouraged me to find a setting where I was best suited to impact the wellbeing of children. She has supported me materially and emotionally. She has patiently and lovingly handled me throughout this process. Quite simply: this does not exist without her. Both of my children were born during my time at the University of Chicago, and they have proved to be bright, hilarious, loving reminders of the reasons that I care about the legal status of children. Clare, now five, empathy embodied. Nora, almost three, ready to take on the world. Thanks as well to my parents, Thomas and Darlene, who have encouraged and supported curiosity, thoughtfulness, and education—in me and in many others. My extended community of family and friends also continue to challenge and support me.

The guiding intellectual force of this work is Fred Wulczyn. The first time that I met with Fred, he listened to me babble about my interests for a bit and then he said, "Have you ever thought about it like this…" And I hadn't. But I do now. I left his office with several books in hand—including Tuma and Hannan's Social Dynamics—and lots to think about. One of the nice things about Fred's continuing mentorship is that he always gives me lots to think about. I am indebted to Fred not only for his assistance on this dissertation, but for the work that he has generated for me within his research group at Chapin Hall, and for the connections within the world of social science research that he has facilitated. Thank you as well to Chapin Hall, and especially members of Fred's research group who provided substantial support and assistance in the collection and processing of the agency data used in this study. Fred's group's dedication over the years of carefully curating the amazing resource that is the Center for State Child Welfare Data deserves special mention. My thanks as well to Mark Courtney, who took an unconventional role in this dissertation, for providing mentorship, criticism, and encouragement.

Mark's depth of subject-matter knowledge was invaluable in understanding the shape of the child welfare literature. Curtis McMillen's enthusiasm to learn is infectious as is his respect for the human element of the child welfare system. Clark Peters, in addition to serving a member of the committee, has also been a great mentor during my time as the University of Chicago. The dedication of Fred, Mark, Curtis, and Clark to the improvement of the lives of children involved in the child welfare system was, and will continue to be, an inspiration for my own work.

I also owe thanks to Deborah Gorman-Smith, Mike Schoney, Evelyn Brodkin, and Scott Allard for advice and training at various stages of my doctoral education. The School of Social Service Administration ("SSA") was a supportive and energetic place to study, and I would like to extend a general thank you to the faculty, staff, support staff (thank you especially to Sid and Alex) and administration for the various ways that they work extremely hard to have created the environment that exists at SSA. My experience at SSA would not have been the same without my fellow PhD students—you were essential to my education, and I have learned so much from all of you and the interesting things that you are passionate about. I want to mention, in particular, Ryan Heath, Theresa Anasti, Julian Thompson, Sameena Azhar, Caitlin Elsaesser-Gantz, Kate Gibson, Alexandra Stanczyk, Aditi Das, and Kevin Tan, along with my other cohort mates Charity Anderson, Daysi Diaz-Strong, Keith Green, Megan Jarpe, Jaesung Kim, and Yuan Lin. Doctoral education is a community effort, and I greatly appreciate the community at SSA.

Matt Orme at the Washington State Center for Court Research was critical in my access to the court data in this study. He helped created the day-level data set that was used in this study, and was very supportive in questions of analysis and interpretation. His work, and his focus on the court improvement, is greatly appreciated. Thank you as well to Tammy Cordova at the Washington State Department of Social and Health Services Children's Administration. She

assisted me both in obtaining the permissions to use the agency data in this study, and in interpreting several peculiarities within the data. Michael Heard at the Washington State Office of Public Defense was one of my primary contacts in the qualitative portion of this study, and was instrumental in introducing me to the origin nodes in both of my study counties. This dissertation would not have been possible without the willing support of the folks in Washington State and their genuine curiosity about the approach. And, importantly, the data used in this dissertation would not exist without the quotidian bureaucratic paperwork done by street-level workers which undergird all of the data sets employed in this dissertation. The data itself is representative of the hours of work that front-line workers put into child welfare.

This is also an appropriate place to thank the partners at Acton & Snyder, LLP, and in particular Tuck Meyer, Tom O'Shaughnessy, and Derek Girton, for supporting my legal career, especially the less remunerative portions. Working in the Vermilion County child welfare system and alongside the people involved therewith—including judges, social workers, attorneys, associated personnel, and the children to whom this dissertation are dedicated—was a critical moment in my life course. That experience—and the willingness of many, many, many people to patiently indulge my questions and conversations about child welfare (thank you especially to Sandy Kopels at the University of Illinois (even though I didn't always follow your advice))—gave me purpose, and laid the groundwork a life's work. And my relationship with the street-level operation of that system continues to provide context for my thinking and for my work.

Abstract

This dissertation builds an empirical justification for the application of systems theory in child welfare research, policy, and practice. This dissertation considers the theoretical question of whether systems structures shape child welfare populations. Synthesizing population ecology theory and social dynamics theory, this study predicts that patterns of entries into and exits out of the child welfare system will manifest themselves differently if entries and exits are constrained by system structures as opposed to if those cases are reviewed individually and independently.

Applying that theory, this dissertation then considers the empirical question of whether observing, in this case using Empirical Dynamical Modelling, the dynamics of child welfare populations over time allows those structures to be inferred. This study focuses on quantitative analysis of child welfare administrative data collected in six Washington State counties between the years 2000 and 2014 within two child welfare subsystems: out-of-home care and dependency court. In order to better contextualize the quantitative analysis in this study, a limited qualitative inquiry focused on bounding the analysis in a meaningful, practice-relevant scope was conducted.

Analysis found some support for coupling of entry and exit behavior both within and between child maltreatment court and out-of-home care subsystems. Relationships were stronger within subsystems than between subsystems. Analysis found nonlinearity across subsystems. Prior to the quantitative analysis, conducted qualitative interviews with thirteen practitioners in two Washington counties identified conditions which could produce feedback, capacity, and rate governing behavior in child welfare systems. Importantly, practitioner reports focused the quantitative analysis on week- and county-level aggregations for quantitative analysis.

This dissertation contributes to social work by conceptualizing and empirically justifying a population-based frame to develop systems thinking in child welfare. Further, this dissertation identifies nonlinearities and coupled relationships in child welfare time series which require methodological reconsideration in child welfare analysis.

Introduction

From 2006 to 2010, I practiced law as a court-appointed guardian ad litem in child welfare cases. That work required me to balance decisions where the best interests of children and families were on one hand and resource constraints which limited those choices were on the other. And those constraints often ran contrary to my ethical obligation to represent a child's best interest—I could not always do what was right, but instead had to choose what was best within available options. In the practice context, those constraints looked like lots of things: inadequate time, under resourced services, under staffed agencies, limited placement options. Those time and capacity constraints directly impacted the lives of my clients, and I was continually struck by the disjunction between what my clients needed and what was available to them.

Jake[1] was a child caught in that everyday tension. His current placement was not meeting his needs. But at that moment there were no appropriate alternative placements available. It was my ethical obligation to view Jake's individual needs and work toward his best interest. I, and other child welfare professionals working on Jake's case, knew that his current placement was not in his best interest. But resource constraints meant that an appropriate placement was not available. So, Jake lingered in a placement that I knew was not in his best interest.

The facts of Jake's case were straightforward: Jake needed a placement that didn't exist, so he stayed in a suboptimal environment. If you believe that social work best practices should require decisions in cases to be based on the needs of individual clients in consideration of those clients' individual contexts, then Jake's case cuts against the ideal that cases are reviewed and worked on their merits alone. Put another way, I was not able to make any decision that I may

[1] Jake is a pseudonym.

have wanted—I could not even make the decision that was clearly best. I was constrained in my actions. In fact, the reality of the ways that demands and resources shift within a practice environment acted to shape the ways that I made decisions.

The tension between what is right and what is possible in child welfare brought me to the research in this dissertation. Though research can and has addressed that question in different ways in individual, organizational, and policy contexts, I frame those constraints in child welfare within the context of systems—a set of components, organized toward a common goal, which exhibit a characteristic set of behaviors as those interconnected components respond to resources and demands. I look for ways in which constraints might manifest themselves within child welfare populations, not by directly observing resources and demands, but by observing entry and exit processes across time and looking for characteristic systems behaviors. Systems thinking leads me to ask whether the constraints on front-line workers' ability to make decisions based solely or mostly on information about individual clients are observable at the systems level. Systems thinking leads me to argue that those systems-level constraints pose a threat to decision making based on individual client characteristics—Jake needed the right bed but the child welfare system could not make that choice because action was constrained by forces outside of that child's individual needs. Systems thinking also provides an opportunity for different thinking about interventions—how is it that we can manage the populations in order to minimize the effect of resource constraints. Ultimately, I hope that the work begun in this dissertation will play a role in helping child welfare administrators and policymakers relieve some of the contextual pressures on front-line workers in the child welfare system, freeing them to make decisions based more completely in the best interest of their individual clients.

To that end, this dissertation represents a first step: an exploratory study to evaluate the usefulness of the systems conception of how constraints shape child welfare practice and how child welfare administrators and policymakers might respond to systems constraints. In it, I present a way of thinking about a way to observe systems structures in child welfare. I then justify that way of thinking by empirically analyzing the relationship between entries and exits in child welfare populations. The goal here is to identify systems structures—evidence of resource constraints, inferred without directly observing those constraints—within changing populations. Those systems structures provide evidence of resources constraints that limit child welfare practice, and by studying population change we can infer the existence of those constraints without directly observing them. This conceptualization and these methods provide a supplement to the already rich individual- and organizational-level analysis in child welfare. Understanding the impact of system structures opens previously untapped conceptual streams in which administrators and policymakers can act to allocate the resources dedicated to and demands placed upon front-line workers in the child welfare practice context.

0.1 Focus of Dissertation

The purpose of this dissertation is to build an empirical justification for the application of systems theory in child welfare research, policy, and practice. Specifically, this dissertation considers the theoretical question of whether systems structures shape child welfare populations and the empirical question of whether observing the dynamics of those populations over time allows those structures to be inferred. Applying population theory, population size is an essential subject of analysis. The size of populations over time is solely determined by entries into and exits from those populations. Empirically, it is within those entries and exits from the child welfare population that this dissertation seeks to detect population behavior and systems structures. In this study, I studied child welfare populations quantitatively using administrative data collected in six Washington State counties between the years 2000 and 2014 within two child welfare subsystems: out-of-home care and dependency court. I supported that quantitative analysis with a narrowly focused qualitative study.

0.2 Key Concepts Defined

This dissertation is concerned with population dynamics in the child welfare system. "Population," "dynamics," "child welfare," and "system" are the foundational concepts of this study, and this section will lay out basic definitions of those terms.

0.2.1 Population

In this dissertation, "population" is defined as the function of the dynamic equilibria between increases (entries into the child welfare system) and decreases (exits from the child welfare system) in that population.[2] There are three relevant populations in this dissertation. First, there is the population of children involved in the child welfare system, defined in this dissertation as both the out-of-home care population and the dependency court population.[3] Second, there is the population of children in out-of-home care. Third, there is the population of children who have an open dependency case in dependency court. These populations are observed between January 1, 2000 and December 31, 2014; and in six counties in Washington State (Clark, King, Pierce, Snohomish, Spokane, and Yakima).

---

[2] Section 1.1.1, infra, elaborates on this technical definition of population, contrasting it to common usage. Chapter 2, generally, is dedicated to outlining more specific definitions of population phenomena.

[3] These populations are defined more completely in sections 0.2.3.2 (for out-of-home care populations) and 0.2.3.3 (for dependency court populations).

0.2.2 Dynamics

This dissertation considers the dynamics of populations.[4] Dynamic thinking conceives of populations in terms of change through time. Dynamic population theory ties the observed size of a population at a given time to the previous size of that population. Thus, a population is coupled to itself across time—as an example, the size of the population today is dependent upon and adjusting to the size of the population yesterday.

Population theory identifies carrying capacity and feedback as two potential mechanisms which relate to how population growth adjusts over time. Carrying capacity is a criterion measure of the sustainable population size given the resource constraints within an environment.[5] Capacities impacting child welfare populations might include such things as public funding, worker time, and the number of placements available, among other things.[6] Feedback connects carrying capacity to entry and exit processes. As the relationship between existing population size and criterion carrying capacity changes, feedback mechanisms adjust the rates at which entries and exits occur (Foster-Fishman, et al., 2007). Theory suggests that these processes, where present, create a context in which decisions about entries and exits are made. Thus contextual, population-level constraints may routinely influence options in child welfare. It is the embeddedness in time that forms the foundation for the feedback exerting influence on the dynamic equilibria between coupled entries and exits.

0.2.3 Child Welfare

The allegation of, or substantiated existence of, child maltreatment authorizes the state child welfare system to intervene in the family where that maltreatment occurred. “Child welfare”

---

[4] Section 1.1.2, infra, elaborates on dynamics in terms of change and time.
[5] Section 2.1.1.1, infra, provides a more detailed definition of carrying capacity.
[6] Section 2.2, infra, provides a detailed description of potential constraints on the child welfare system.

is the legal system of intervention in and prevention of child maltreatment.[7] This section will provide general background into the child welfare system and definitions of "child maltreatment," "out-of-home care," and "dependency court."

Child welfare includes, among other things, child protective services which investigate allegations of abuse and neglect, along with child welfare workers who intervene in and treat family systems impacted by child maltreatment. One job of child welfare is to assess whether a child can be safely maintained in the home of their parent or guardian, and, if not, to remove that child from that home and place them in alternative care—out-of-home care—and monitoring that placement for its duration. These protection, investigation, and casework activities take place within a state agency or a state agency plus a network of state-authorized private agencies. The child welfare universe, however, is broader than protection, investigation, and casework, and also comprises the broader universe of services directed toward the intervention in and prevention of child maltreatment. This also includes court systems—judicial officers, attorneys, and court personnel—which authorize some intervention activities and review other intervention activities. Though the child maltreatment system refers to the broader state-authorized system of prevention and intervention, this dissertation focuses mainly on two subsystems within that larger system: out-of-home care and dependency courts.

0.2.3.1 Child Maltreatment

The term "child maltreatment" refers, in a general sense, to harm caused to children by any person. For this dissertation, "child maltreatment" refers to the concept of state-defined harm to children for which there is associated state authority to act through the child welfare system, and specifically through out-of-home care placement and dependency court systems. Though

[7] Section 3.1, infra, provides a more comprehensive overview of the child welfare system as relevant to the specific Washington State case.

they hold commonalities across the United States, definitions of maltreatment are state specific. In Washington State, legal definitions of child maltreatment apply to minors under the age of eighteen, and comprise harmful conduct directed at minors by any person or harmful omissions by a person responsible for that child. Harm can include actual harm or risk of harm to a child's health, welfare, or safety. The conduct can include physical, sexual, or emotional abuse. Neglect includes failure to provide adequate food, shelter, and clothing; chronic failures to discharge parental obligations; cumulative parental behaviors which indicate a disregard for a child's physical, emotional, or developmental wellbeing; and actions or failures to act which create a risk of harm to a child's physical, emotional, or developmental wellbeing (Revised Code of Washington §14.1; Revised Code of Washington §26.44.030; Washington Administrative Code §388-15-11).

0.2.3.2 Out-of-Home Care

"Out-of-home care" is used to describe any placement setting utilized by the child welfare system as an intervention for an incident of child maltreatment where a child cannot be safely maintained in the home of their parent or guardian. Out-of-home care placements are authorized, and then reviewed, by judicial officers in dependency court. Out-of-home care can take place in many different settings, including relative foster care, traditional foster care, group care settings, or others. However, this dissertation does not differentiate between types of out-of-home placements. Out-of-home care begins when a child is removed from home and placed in care. It ends when the child is returned home to parents or guardians, is adopted or placed in a legal guardianship, becomes independent after achieving the age of majority, runs away without returning to care, or the placement otherwise ends for other reasons. For the duration of the placement, a child is said to be in out-of-home care, and it is this key designation—placement—which differentiates some children from other children in this dissertation.

0.2.3.3 Dependency court

This dissertation will refer to the judicial entity that provides judicial authorization and review for out-of-home care placements as "dependency court," though it has different names in different jurisdictions. The fact that out-of-home care placements are authorized and reviewed by judicial officers as part of an adversarial court proceeding forms an essential conceptual link between out-of-home care and dependency court. Thus, dependency court and out-of-home care populations are not mutually exclusive. Instead, they are interwoven.[8]

Dependency court is a judicial institution in which allegations of child maltreatment are adjudicated and reviewed. Decisions in dependency court are made by a judicial officer, with participation from attorneys for the state, parents and their attorneys, and potentially representatives of the children or child welfare agency. The totality of cases under review by the court comprises the court population. A case enters dependency court upon the filing of a petition, this is referred to here as a "case opening"; a case exits upon a judicial action which terminates that case, referred to here as a "case closing." This dissertation will use the convention of referring to dependency court cases as "opening" and "closing" when necessary to differentiate between the more general language of "entry" and "exit." So long as a case is open, a child is said to be involved in dependency court. Similar to the concept of placement in the out-of-home care system, having an open case in dependency court is a designation which differentiates one group of children from other groups of children.

[8] One way that child welfare systems differ across jurisdictions is in the overlap between out-of-home care and dependency court populations. Some jurisdictions have a great deal of overlap between the populations, which others have less. Typically, the dependency court population is larger than the out-of-home care population. This occurs because there are dependency court cases where there are not current out-of-home care placements. On the other hand, there are some jurisdictions in which certain short-term or voluntary out-of-home care placements occur without co-occurring in the dependency court population. This is discussed in the Washington State context in section 4.1.3, infra.

0.2.4 System

I have mentioned that out-of-home care and dependency courts are sub-systems of the larger child welfare system. For the purposes of this dissertation, “child welfare,” “out-of-home care,” and “dependency courts” are all systems not only in a colloquial sense, but in a technical sense. A system is “[a] set of elements or parts that is coherently organized and interconnected in a pattern or structure that produces a characteristic set of behaviors, often classified as its ‘function’ or ‘purpose’” (Meadows, 2008, p.188). Systems are adaptive (Forrester, 1995). This dissertation concerns itself with endogenous adaptation—that is, adaptation which is brought about by within-system influences. In child welfare, both courts and out-of-home care operate as systems (Wulczyn, et al., 2010). Both courts and out-of-home care possess coherently organized elements which are directed at the common goal of child protection. Courts and out-of-home care exhibit characteristic, purposive behaviors toward the goal of child protection.

0.3 Summary of Theory

A synthesis of population ecology theory and social dynamics theory suggests that systems structures shape child welfare populations. Ecological theory directs our attention toward the critical features within population-level analysis. Social dynamics provide a grounding for the conceptualization of change in populations as a marker for the underlying social systems. The theoretical underpinnings are most simply described by a conceptual model illustrated as a system of coupled difference equations. The conceptual model illustrates a way over time in which a population adjusts, at some rate, to capacity constraints and prior size of the population to produce increase (or decrease) of population:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r'[\pi' x(t) - y(t)] \tag{0.1}$$

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = r''[\pi'' y(t) - x(t)]$$

where the entries, y, into and exits, x, from the child welfare system are defined by the function's dynamic, interrelated processes governed by capacity, π, and rate, r, parameters. Capacity is the measure of the sustainable population size given the resource constraints within an environment.[9] Rate is the mechanism through which feedback processes link capacity and change in population size.

The conceptual model allows us to observe the coupling of entry and exit processes, the importance of the criterion carrying capacity and the feedback systems within the coupled equations, and the dynamic nature of the coupling, carrying capacity, and adjustments. Thus, more specifically, when we consider the change in entries, y, over time t, we see that that is a function of the rate parameter, r, multiplied by the difference between the number of entries, y, at t and the number of exits, x, at t adjusted by the capacity parameter, π. The change in exits, x, operates similarly. It has own rate parameter, r, multiplied by the difference between the number of exits, x, at t and the number of entries, y, at t adjusted by the capacity parameter, π. It is the presence of the entries in the exit equation and the exits in the entry equation that drives the population behavior from which we can infer the influence of a common set of capacity constraints.

Entries are determining exits and exits are determining entries through the common mechanisms of rate and capacity. The significance of this relationship is that it raises the possibility that there are complex relationships between variables in the time series, including

[9] Defined in section 0.2.2, supra.

nonlinear relationships.[10] Whereas relationships are proportional—that is entries, y, change as some proportion of exits, x, in nonlinear systems, entries, y, do not vary directly in some proportion to exits, x. Nonlinear relationships may display dependencies, multiple equilibria, and chaotic behavior which shift as structural features of the system change (Tuma & Hannan, 1984).

0.4 Thesis Statements

Based on those theoretical propositions, the patterns of entries into and exits out of the child welfare system will manifest themselves differently if entries and exits are constrained by system structures as opposed to if those cases are reviewed individually and independently. Thus,

1) Structured population behavior in the child welfare system will be apparent in coupled entry and exit dynamics within population-level time series.

In other words, what I ask is whether out-of-home care entries influence out-of-home care exits, because, if so, that relationship provides some evidence of a structure that bounds the system's ability to take in or return home children. "Structure" in this sense refers to some group of resource constraints which regulate child welfare practice.

To test this within-subsystem hypothesis, I analyzed time series behavior within out-of-home care and within the dependency court. I examined individual entry and exit time series to see if they have structure. If time series are random, i.e., they lack structure, that provides some evidence of the lack of system effects under this hypothesis. Contingent on the identification of nonrandom structure, I tested whether time series are coupled—that is, whether entry time series work in conjunction with exit time series (and vice versa). Theory predicts that the nonrandom coupling of entry and exit time series is evidence of a shared causal influence. Theory further predicts that the shared causal influence may be a resource constraint.

[10] For an extended discussion of nonlinearity in coupled dynamic time series, see section 2.1.3, infra.

The child welfare system is comprised, in part, of the out-of-home care placement subsystem and the dependency court subsystem. If the population processes within dependency courts and out-of-home care are intertwined, then

2) Out-of-home care subsystems and dependency court subsystems interact at the population level and constraints on one subsystem will manifest themselves in coupled population-level time series for the other subsystem.

For example, what this asks is whether entries into out-of-home care are related to entries in dependency court. If relationships exist between entries into out-of-home care and entries in dependency court, I can test to see if those relationships exist because the same forces—resource constraints—influence both subsystems.

To test this between-subsystem hypothesis, I examined time series behavior between out-of-home care and dependency court. I tested for coupling between variables in the out-of-home care and the dependency court subsystems. Evidence of coupling suggests a common causal influence between those subsystems, which means that in order to understand the resource constraints within the out-of-home care subsystem that one must consider the dependency court system and vice versa.

In order to better contextualize the quantitative analysis in this study, I conducted a limited qualitative inquiry focused on bounding the analysis in a meaningful, practice-relevant scope.

0.5 Summary of Major Findings

Quantitative analysis found some support for the theses.

Individual entry and exit time series contained evidence of nonrandom structure. That is to say that analysis detected some evidence that observed population processes are structured by constraints which act to pattern actions within child welfare. Focused first on coupled entry-entry, exit-exit, net-net (net population change—entries minus exits), and total-total (total weekly volume—entries plus exits) dynamics in population-level time series, results from nonparametric analysis indicate some degree of lagged coupling in all time series across counties ranging from weak to moderate. There was weaker evidence of structured nonrandomness in linear analysis. However, child welfare time series displayed near-ubiquitous nonlinearity in all six counties when examining entry and exit time series, which indicates that there is more complex behavior in the coupling of the entry and exit variables than simple proportional linkage.

There was evidence of within-system coupling in some, but not all, time series. This means that in some cases structured patterning similar to that observed in the univariate time series was observed in bivariate relationships within the same subsystem. Analysis found nonrandomness in coupling within subsystem time series (e.g. entry-exit; entry-net; exit-total). The strongest evidence of this nonrandomness was in the moderate relationship between week-to-week entry/exit dynamics and net population change. Similarly, moderate relationships were found between week-to-week entry/exit dynamics and total weekly entries plus exits, and between net and total series. There is weak, but extant, coupling in entry/exit dynamics in two thirds of the tested systems.

Evidence for the between-subsystem hypothesis was more mixed. Analysis did confirm a critical, and expected, link between court case filings and out-of-home care placements in five of the six counties. However, there was weaker evidence of other coupled nonrandom behavior between out-of-home care and dependency court, and only in half of the counties studied. This suggests that within the context of this study that resource constraints in out-of-home care may not be related to case openings and closings in the dependency courts.

Quantitative results are mainly limited by the ability to identify the proper time lag which structures the coupling, the question of whether entry/exit dynamics serve as the proper indicator, and the selected temporal and geographic scope of this project. However, these results do point to the utility of population-level analysis, provide some evidence of population-level structuring of child welfare practice, and suggest some directions for future research using population dynamics.

Prior to the quantitative analysis, I conducted qualitative interviews with thirteen practitioners in out-of-home care and dependency court systems in two Washington counties. The purpose of these interviews was to locate the quantitative analysis in a practice context and to analyze participant narratives for consistency with population thinking. These interviews lent support to the practice relevance of conceiving of populations as one significant structure in child welfare. Participants reported that the conditions which could produce this feedback, capacity, and rate governing behavior are explicitly present in the dependency courts and out-of-home care systems. Street-level practitioners reported that they think about populations; talk to other practitioners, formally and informally, about those populations; and respond to population fluctuations. In addition, street-level practitioners noted that entries and case openings serve, along with caseload and perceived workload, as important indicators of population.

0.6 Summary of Contributions to Social Work

This dissertation contributes to academic social work in two major ways: First, the existence of nonlinear relationships within child welfare time series calls for a reassessment of methods which analyze trajectories of child welfare populations across time. When relationships between variables in time series are nonlinear, those relationships may appear random when using linear methods. Nonlinear methods are thus required to identify relationships in nonlinear systems. A principle reason for this distinction is that predictive, or forecasting, models can be created to describe nonlinear systems whereas random linear systems are highly resistant to predictive modelling (Sugihara, et al., 2012). The findings of this dissertation lay some groundwork for the expansion of systems research in child welfare, and provide some introduction to nonlinear forecasting models which may assist agencies and policymakers appropriately deploy resources.

Second, the conceptualization of a population-based frame and the study's empirical findings provide justification for a research program that employs dynamic population-level tools. It provides some of the primary research necessary to continue to develop populations thinking in the child welfare system. Moreover, this dissertation applies methodology developed in theoretical ecology in a novel way, and finds some support for the application of that nonparametric methodology.

From a practice standpoint, the primary audience for this dissertation includes child welfare administrators and policymakers, concerned with managing resources within the child welfare system. Administrators and policymakers set the broad parameters of resources like time and capacity that the system is continually responding to. Additionally, this dissertation suggests a possibility for using nonparametric tools for short-term forecasting in child welfare planning which could assist in revealing potential population changes in the immediate future. This dissertation also contributes generally to a systems perspective of child welfare practice where the child welfare system itself is an integral component.

0.7 Organization of this Dissertation

This dissertation will proceed as follows: The first two chapters will focus on the problem of populations in a general case. Chapter 1 will introduce the child welfare system in Washington

State. Chapter 1 will then lay the conceptual foundations, rooted in social and population dynamics, that motivate research questions about whether there exists in child welfare predictable, population-level coupling of entry and exit behavior which may be explained as a manifestation of a latent accumulation of resource constraints, feedback, and adjustment mechanisms within the system. Chapter 2 will refine those conceptual foundations into an approach to answering questions concerning population systems in child welfare, concluding in specific hypotheses.

After that groundwork is laid, the dissertation will turn to a specific case application in Washington State. Chapter 3 describes a limited qualitative inquiry into the street-level salience of population context, feedback, and adjustment as they relate to the heuristic presented in Chapter 2. Chapter 4 provides description of fifteen years of child welfare entry and exit data drawn from out-of-home care systems and case opening and closing data drawn from the dependency courts in six counties in Washington State. Building on the preliminary information about the data developed in Chapter 4, Chapter 5 describes a method of nonparametric analysis, Empirical Dynamical Modeling, which is suited to investigating weakly coupled dynamic systems. Chapter 6 presents the results of analysis, indicating an existent, practically and statistically significant, systems signal which partially explains the variance across time in child welfare time series. This dissertation concludes with Chapter 7, providing analysis of the results in Chapter 6 and discussing the implications of those results for social work practice and research.

Chapter 1:
Foundations

This dissertation considers population dynamics in the child welfare system and the structures that those dynamics allow us to observe. For example, when we observe the children who are entering out-of-home care in a given week and then observe exits from out of home care in a later week, do we see a linkage (or a coupling; patterning)? If so, that suggests the possibility of a structure: that is, that the relationship between entries and exits is somehow influenced by the size and composition of that population as it moves through time. The scope of this project, then, is limited to population thinking: the conceptualization and analysis of population-level characteristics and dynamics in child welfare. This chapter will contain a basic description of the child welfare system in Washington State, and illustrate some foundational population concepts which justify the application of population thinking to child welfare.

Populations present a unique set of observable phenomena and dynamics. Unique, in this sense, means that the behavior[1] of populations operates distinctly from the characteristics and dynamics of individuals which comprise them—that is, the behavior of populations is not merely the sum of the behaviors of individuals; and population phenomena appear at the population level but not for any particular individual.[2] For the purposes of this dissertation, populations, population thinking, and population phenomena act to form a "methodological doctrine" which

[1] In this dissertation, when I refer to "behavior," I am referring to the behavior of the population as a whole and not of individual members of that population.

[2] Situating population questions as distinct from questions about individuals creates a hierarchical question (Billari, 2015): What is the relative influence of attributes relevant at the individual level? What is the relative influence of the attributes relevant at the population level? Even this formulation, however, begs the question of population as relevant empirical subject. This dissertation is limited in scope to addressing the predicate question of whether child welfare populations make sense as an empirical subject in a practice relevant context. The hierarchical questions are essential, but understanding the behavior of the population system is prior to addressing those multi-level questions.

This dissertation is not about proper units of analysis. In fact, I conceive of individuals and populations as among the proper units of analysis for research into child welfare. The exclusive focus on population here is an effort to highlight the potential importance of aggregate units of analysis.

focuses on the population behavior that emerges from the aggregate activities of individuals, but which is not the sum of those activities (Ariew, 2008, p.9). As such, this dissertation applies population thinking, situating child welfare populations as a theoretical and empirical subject which have analyzable properties that impact child welfare practice. Population-level analysis focuses on the unique characteristics of populations and promises to supplement individual-level child welfare analysis by explaining features of the child welfare system that are not immediately reducible to the experiences of individual children, workers, or organizations.

Populations are within and related to the system of child welfare practice, and accounting for the unique properties of population is necessary for a more complete understanding of child welfare policy and practice. The key proposition that populations have unique properties finds roots in one of the central theoretical constructs of the social work profession: the eco-systems perspective. The eco-systems perspective frames the analysis of individuals within their social environment and conceptualizes that environment as shaped by system forces from the most proximal, such as family and interpersonal systems, to the more distal, policy and society (Meyer, 1983; Bronfenbrenner, 1979; Richmond, 1917). Child welfare populations fit into that model as part of the exosystem. The exosystem, settled between the immediately proximate microsystem and the distal macrosystem, is broadly defined by as containing forces which impact the immediate context of the family being served (or the caseworker who is serving that family), but in which the family (or caseworker) does not have an immediately active role (Green & McDermott, 2010; Meyer, 1983). Child welfare organizational factors are generally situated within the exosystem as part of the service systems for change domain, where focus is on the operation and delivery of interventions and how those interventions are organized (see Brekke, 2012; Tucker, 1996). Population dynamics can serve as another analytic leverage point that can be used to understand exosystem influence on individual children and families who are engaged with the child welfare system.

This is a similar approach to that which is taken studying the expansion and contraction of biological populations in theoretical ecology. The interrelationship between a population and its environment is partially determinative of the possibilities of that population within that environment. Being able to identify some of the partially determinative pieces of that puzzle assists in understanding the growth and decline of biological populations, or more specifically the structural constraints which are placed on that growth or decline as properties unique to a particular population-environment interaction. The ebbs and flow of populations provide meaningful insights into the constraints those populations are under, even if the constraints themselves are not observable. Thus, drawing as well from the theory of social dynamics,

> [w]hen the size and the structure of the caseload are compared across geographic areas or from one moment in time to the next, findings reveal patterns that are linked to underlying population differences, policy initiatives, and socioeconomic conditions. The purpose of analyzing aggregate-level dynamics is to identify patterns of change and understand the reasons why the size and structure of the caseload fluctuate over time

(Wulczyn, 1996, p. 320). The conceptual and methodological approach of ecology and social dynamics in understanding the behavior of populations forms the foundation of this dissertation.

This chapter begins by providing background information about the child welfare system that is the focus of the present study. This chapter will then review the theoretical underpinning of where within populations those important change patterns can be revealed. This chapter will review the fundamentals of population ecology and its relationship to social dynamics. Following the articulation of a broad research question, Chapter 2 will take up the task of the framing of concepts laid out in the chapter as a theory of problem solving for population problems in child welfare.

1.1 Context of the Present Study

The context of the empirical component of this study is the child welfare system in six counties within Washington State. This section proceeds in two parts. First, I give a brief description of Washington State and the study counties. Next, I provide background information on the child welfare system in Washington State, focusing on critical players and points within the system.

1.1.1 Washington State and Study Counties

Washington State is located in the Pacific Northwest. Within Washington, there are thirty-nine counties that range from densely populated urban and suburban areas with robust social service networks to lightly populated rural areas where hours of travel may be required to access services. During the period in which data from this study was drawn, Washington had a total population of 6.7 million and a child population of approximately 1.5 million. (US Census Bureau, 2010 Census). As will be discussed in depth in Part 1.1.2, *infra*, child welfare in Washington is managed at the state level. The Children's Administration, within the state Department of Social and Health Services, is an executive agency responsible for public child welfare, and, consequently, out-of-home placements, in Washington. During the study period, the out-of-home care population was approximately 10,000. The majority of these cases are concurrently open within county-level court systems.[3] Approximately 6,000 children entered and 6,000 children left the out-of-home care population annually (US HHS, 2014a; 2014b; 2014c).

[3] The relationship between courts and out-of-home care will be described in more depth within Section 1.1.2, *infra*.

The Children's Administration directly delivers child welfare services through local offices managed within three regions, each broken into a north component and a south component. Region 1 comprises the whole of the state to east of the Cascade Mountains. This large, 20-county region, is sparsely populated outside of urban centers in Spokane and Yakima Counties. Region 2 includes the east coast of Puget Sound, including King and Snohomish Counties, and most of the islands to the north and west of Seattle. Region 3 contains the counties on the Pacific Coast, and those to the west and to the south of Seattle.

This dissertation focuses on six counties: Clark, King, Pierce, Snohomish, Spokane, and Yakima. These counties represent the five most populous counties in Washington, along with Yakima. Together, these six counties represent approximately sixty percent of the total weekly average number of children in out-of-home care in Washington State. King County is the largest county in Washington and the home of the metropolitan center of Seattle, the largest population center in the state with suburbs that extend into adjacent counties. King has a population of approximately two million, with approximately 460,000 minor children.[4] King comprises the Children's Administration's Region 2 South. During the study period, King County averaged twenty-one entries into and twenty-two exits out of out-of-home care. In the court system, there were, on average, fourteen case openings and fifteen case closings per week.[5] Directly to the north of King County is Snohomish County, which includes some northern suburbs of Seattle and Everett. Approximately 700,000 people, including just under 200,000 children, live in Snohomish County. Snohomish is within the Children's Administrations Region 2 North. Weekly average population change in Snohomish County was eleven entries into and eleven exits out of out-of-home care; while there were nine dependency court cases opened and closed.

---

[4] Population estimates in this section are drawn from the 2010 US Census.

[5] More complete summary statistics are available in Appendix A

Directly to the south of King County is Pierce County. Tacoma is along Puget Sound in western Pierce County, and in the easternmost part of the county is Mt. Rainier. Pierce County is home to a large military base: Joint Base Lewis-McChord. About 800,000 people live in Pierce, including approximately 220,000 children. Pierce is within the Children's Administration's Region 3 North. In the Pierce County child welfare system, the weekly average for entries and exits was twenty, while, on average, eleven dependency cases opened and ten dependency cases closed. Yakima County adjoins Clark County to the east of Mt. Rainier, including some of the eastern slopes of the Cascades, and extends along the Oregon border to the south. Within Yakima County lies the Federally recognized lands of the Confederated Tribes and Bands of the Yakima Nation. The population of Yakima County is approximately 250,000 people, including approximately 80,000 children. Yakima is within the Children's Administration's Region 1 South. In the out-of-home care system in Yakima County, the weekly average entries and exits during the study period were nine, and the dependency court opened and closed four cases on average. West of Yakima and south of Pierce along Washington's border with Oregon is Clark County. Clark County is bordered on the west and the south by the Columbia River, and includes areas of suburban Portland, Oregon. Clark County is home to approximately 425,000 people, including about 125,000 children. Clark is within the Children's Administration's Region 3 South. Clark is the only study county which is not the home of its respective regional office. The Region 3 South office is located in Thurston County. During the study period, every week Clark County averaged twelve out-of-home care entries and twelve exits, while five dependency court cases opened and four closed. The state's capital of Spokane is the central feature of Spokane County, located in the westernmost region of Washington, along the border with Idaho. Spokane is within the Children's Administration's Region 1 North. Spokane County is the only county in the sample which does not contain an autonomous Native American government or Native American reservation. In Spokane County, the weekly average for entries into and exits out of out-of-home care was fourteen, and ten dependency court cases opened while nine cases closed.

1.1.2 Introduction to the Washington State Child Welfare System

This section, focusing on written policy, will trace the trajectory of a child welfare case in Washington from initial report, through administrative and judicial processes, identifying the key roles and decision points.

1.1.2.1 Report and Investigation

State response to the maltreatment of children is typically initiated by a report to the Washington State Department of Social and Health Services Children's Administration (hereafter "Children's Administration").[6] Reports of maltreatment are either made to a central hotline or to one of the Children's Administration's approximately forty-six local offices located throughout Washington State. The Children's Administration is mandated to record and investigate reports of child maltreatment (Revised Code of Washington §26.44.030). Those investigations are conducted by Child Protective Services (hereafter "CPS"), a subdivision of the Children's Administration. CPS maltreatment investigations require an in-person response to moderate- and high-risk cases where the alleged victim and alleged perpetrator are contacted by CPS, and the agency makes an attempt to determine whether the alleged conduct meets the definitions for maltreatment and whether the child is at risk for serious harm if left in the custody of the parent, guardian, or custodian (Washington Administrative Code §388-15). CPS aims to

[6] Legislation due to take effect on July 1, 2018, will recast the Children's Administration as the Department of Children, Youth, and Families (Department of Children, Youth, and Families—Creation, House Bill 1661, 65th Washington State Legislature (2017)). All statutory and administrative law citations in this section refer to law in effect from February 10, 2003 through July 1, 2018. Prior to the last major statutory revision in 2002/2003, the framework of the child welfare intervention process was similar in spite of some differences in details (see VanMeter, 2004, 863–866).

conclude their investigation within forty-five days[7] and notify the alleged perpetrator in writing of the findings of that investigation (Washington Administrative Code §388-15-021; §388-15-065). Alleged perpetrators have the right to administratively appeal any determination of CPS within the Children's Administration (Washington Administrative Code §388-15-021).

Though not a subject of the present study, the reader should know that the Children's Administration also provides non-placement intervention through family preservation services (designed to maintain children at risk for out-of-home care placement in the homes of their parent, guardian, or custodian) and family assessment response[8] (designed to voluntarily assist the parent, guardian, or custodian and connect them to community supports, and provided as an alternative to the investigation services above). The Children's Administration also administers family voluntary services (designed to voluntarily assist parents, guardians, or custodians in the prevention of child maltreatment or with issues related to child maltreatment after an investigation has been conducted) which can result either in a non-placement voluntary services agreement or a placement, in limited circumstance, through a voluntary placement agreement. Voluntary placement agreements will be discussed in Section 3.1.2 below.

1.1.2.2 Out-of-Home Placement; Dependency Court; Attorney Roles

The Children's Administration is authorized to manage out-of-home care placements for child victims of maltreatment in Washington State (Revised Code of Washington §74.13.029). There are three main mechanisms by which children are placed in out-of-home care by the Children's Administration: voluntary placements, emergency placements, and court-ordered

[7] This can be extended to ninety days some circumstances.
[8] Family assessment response services began in 2014 in twelve counties, including three study counties: Spokane, King, and Pierce.

placements. Voluntary placements and emergency placements will be discussed in this section. Court-ordered placements will be discussed in Section 3.1.3, below.

A voluntary placement agreement allows parents, guardians, or custodians to consent to short-term out-of-home care placements for minor children.[9] In large part, children placed under a voluntary placement agreement enter into out-of-home care without court order or court supervision (Washington Administrative Code §388-826-0001, et seq.; see also Courtney & Hook, 2012). Voluntary placement agreements can be terminated at any time by parents, guardians, or custodians. If the Children's Administration determines that there is still a risk to the minor upon termination of the voluntary placement agreement, it can seek a petition in dependency court as described below.

If, at any point during the investigation, CPS determines that the child is at risk for serious harm, then law enforcement may remove that child from the care of their parent, guardian, or custodian and place that child into out-of-home care without a court order (Revised Code of Washington §26.44.050; Washington Administrative Code §388-15-037). This emergency custody is referred to as shelter care, and requires judicial review of the placement within seventy-two hours of custody being taken (Revised Code of Washington §13.34.060).[10] That court review takes the form of a shelter care hearing (Revised Code of Washington §13.34.065). Shelter care hearings, along with all dependency court proceedings, are conducted in Washington State Superior Court. Superior Courts (herein referred to as "dependency courts" when performing their adjudication and review of child welfare cases) are the trial courts of general jurisdiction, with one of extending jurisdiction over each of Washington State's thirty-

[9] Or for youth older than eighteen to request to stay in out-of-home care beyond their nineteenth birthday.

[10] If an order permitting continued out-of-home care placement is not entered within seventy-two hours (exclusive of weekends and holidays) of when the child was taken into emergency custody, then the child "shall be released" from out of home care (Washington State Juvenile Court Rule 2.2).

nine counties. In the Superior Courts, the presiding judicial officer is either an elected judge or an appointed commissioner—and those judicial officers preside over the judicial juvenile proceedings at issue in this dissertation.

In addition to judicial officers, shelter care hearings also typically involve attorneys who represent the interests of Washington State and parent attorneys. The Office of the Attorney General (hereafter "OAG") represents the Washington State through assistant attorneys general. The OAG is a state agency with local offices which provide attorneys for dependency court proceedings. Parent attorneys come in three different types: private pay attorneys, who are hired by and paid for by the parent; private pay attorneys who are appointed through the Parental Representation Program[11], who are contracted by and paid by Washington State through the Office of Public Defense (hereafter "OPD"); or locally appointed public defense attorneys appointed through the county-level public defender's offices referred to by various names in different Washington counties who are paid through a mix of state and local funds. In 2000, the Parental Representation Program began as a pilot program in two counties, including one study county, Pierce. Subsequently, that program expanded to four other study counties (fifteen total counties) in 2005/2006 (Courtney & Hook, 2012).[12] Parent attorneys are appointed by the judicial officer to represent indigent parents who cannot afford to pay an attorney.

In addition to the Assistant Attorneys General and the parent attorneys, during the shelter care the judicial officer will assess the need for, and possibly appoint, a child representative in the form of a lawyer for the child, a guardian ad litem, or a Court Appointed Special Advocate

[11] For a detailed review of the Parental Representation Program and its effectiveness, see Courtney and Hook (2012).

[12] Beginning in July 2018, the Parental Representation Program has been expanded to all Washington State counties (Washington State Office of Public Defense, 2018).

(CASA)[13] (Revised Code of Washington §13.34.065; Washington State Juvenile Court Rule 9.2(c)). Appointed lawyers for children and guardians ad litem are paid and contracted by the court at the county level, and are appointed by judicial officers. CASAs are typically volunteers, and are also appointed by judicial officers. In typical practice, child representatives are not present at shelter care hearings, instead they receive their appointment before the fact finding hearing.

The primary purpose of the shelter care hearing is to review whether the Children's Administration reasonable cause to believe that maltreatment occurred, and to establish whether out-of-home care is necessary for the safety of the child (Revised Code of Washington §13.34.065). At the conclusion of the shelter care, the judicial officer can enter an order which permits the child to remain in out-of-home care. Alternatively, the judicial officer can order that the child be returned to the home of the parent, guardian, or custodian, producing an exit from out-of-home care.

1.1.2.3 Fact Finding and Dispositional Hearing

Following a shelter care hearing, the dependency court will calendar a fact finding hearing. A fact finding hearing must be scheduled—colloquially referred to as "being placed on the docket" or "put on the court call"—within seventy-five days of the filing of the dependency petition (Revised Code of Washington §13.34.070). Shelter care hearings, however, do not initiate all dependency court cases or dependency petition filings. If, at any point during the investigation, CPS determines that court intervention is necessary for the protection of the minor child then the Children's Administration can seek a petition in dependency court (Washington

[13] The nuanced differences in these roles are beyond the scope of this dissertation. For a review, see Duquette (2000) and Duquette and Haralambie (2010).

Administrative Code §388-15-041). This is typically accomplished by referring the case to the OAG, who then files a dependency petition with the dependency court.

Additionally, between the initial investigation stage, conducted by CPS, and the filing of a dependency petition, the child and family are assigned a caseworker from the Children's Administration's Child and Family Welfare Services (CFWS) division. CFWS caseworkers and supervisors are responsible for case planning, service planning, and placement supervision during the pendency of the dependency case (throughout this chapter references to "caseworkers" or "social workers" are to CFWS caseworkers unless otherwise indicated). They produce social histories/social studies/predispositional reports and case service recommendations for dispositional hearings and periodic review hearings, discussed below. CFWS caseworkers provide the primary point of contact between the child welfare system and children and parents, guardians, and custodians.

A fact finding hearing is where the state establishes the underlying claims of the dependency petition. The state, through the OAG, has the burden of proof, by a preponderance of the evidence, to prove the allegations in the dependency petition (Revised Code of Washington §13.34.110). The central question of a fact finding hearing is focused on whether allegations of maltreatment can be proven by the state. Evidence from CPS investigators is typically presented. Parent representatives and child representatives are participants in fact finding hearings and are allowed to present independent evidence, rebut evidence presented by the state, and make arguments. Following the presentation of the evidence and arguments, the judicial officer enters an order with findings of fact and law. If the judicial officer finds that the state has met its evidentiary burden, the court will adjudicate the child dependent. This finding creates the legal basis for the intervention of the Children's Administration. If a child is adjudicated dependent then the court will immediately set a dispositional hearing to be held immediately following the fact finding hearing.[14] If, on the other hand, the court finds that the state failed to meet its evidentiary burden, the court will order the proceeding closed. This order also effectively terminates any out-of-home care placement.

A dispositional hearing is focused not on the allegations of maltreatment, but instead on the plan to correct the conditions which led to the filing of the petition. During a dispositional hearing the judicial officer will hear evidence, presented by the OAG, parents representatives, and child representatives about the placement of the child, services planned for the family, a permanency plan for the child, and other matters related to child wellbeing. The court will also rely on a predispositional report, called an Individual Service and Safety Plan, produced by a CFWS caseworker which outlines the service plan and justification for that plan. At the conclusion of the dispositional hearing, the court will enter an order related to that service plan. In addition, the judicial officer will include, in the dispositional order, orders related to the placement of the child—whether in the home of the parent, guardian, or custodian, or in out-of-home care (Revised Code of Washington §13.34.130). A child not placed in out-of-home care prior to the dispositional hearing can be placed into out-of-home care by judicial order at the dispositional hearing. At the conclusion of the dispositional hearing, the court will set the first periodic review hearing which must occur within ninety days of the dispositional order or six months after the initial out-of-home care placement, whichever is first (Revised Code of Washington §13.34.138).

[14] Though, with good cause, dispositional hearings may be held within two weeks of the fact finding hearing.

1.1.2.4 Periodic Review; Other Exits from Care and Case Closings

The purpose of periodic review hearings is to evaluate the status of the dependency case as it relates to progress toward permanency, compliance with services, and the status of out-of-home care placements. Periodic review hearings must be conducted every six months following the initial review hearing (Revised Code of Washington §13.34.138). Prior to these periodic hearings Children's Administration caseworkers produce progress reports which include recommendations about case progress. At the hearings, evidence may be presented by the OAG, parents representatives, and child representatives as to the status of the case. At the conclusion of the periodic review hearing, the court will enter an order which may continue or revise the current service plan and out-of-home placement. Alternatively, the court can conclude that the goals of the case service plan have been accomplished and order the case closed. Thus, during the pendency of dependency cases, periodic review hearings offer the opportunity to place children in out-of-home care or to terminate those placements and return the child to the home of parents, guardians, or custodians. During these hearings, a court can close dependency cases, including cases where permanency has been achieved though adoption, guardianship, or attainment of the age of majority. When permanency has been achieved through adoption, guardianship, or attainment of the age of majority, the out-of-home care placement is deemed to have concluded. Other events which lead to dependency court case closings and out-of-home care exits are the transfer of cases between jurisdictions and the death of the child.

1.2 Theoretical Grounding

The study of population ecology starts with a very simple insight: The number of individuals in biological populations is increased by births and decreased by deaths.[15] It is the ratio of births to deaths within a given time which determines whether a population is growing or shrinking. Consequently, by understanding the interrelationship between births and deaths, we can understand the change processes of populations without necessarily understanding the underlying individual-level processes that lead to the births or deaths of members of that population. Population change processes are defined in terms of rate of growth or decline and the sensitivity of that rate to capacity criterions—and it is those processes which can serve as partially determinative components of overall population size. Moreover, there is an explicit assumption of a resource-governed equilibrium set by the relationship between a population and its environment which acts upon those population change processes (Ariew, 2008; Coulson & Godfray, 2007).

Wulczyn (1996) observes that related population structures and processes exist in child welfare. Specifically, out-of-home care populations are increased by entries into the system and decreased by exits from the system. Thus, it is possible that change processes in the child welfare system may be described by the interrelationship of entry and exit processes, growth rate, and capacity. Much like a biological system, then, understanding the recapitulation of out-of-home care populations may, in part, be determined by these population processes, and can be predicted without understanding the individual-level processes which lead to entries into or exits from out-of-home care (Ariew, 2008). This bears a relationship to resource dependency theories as deployed in the study of organizations. Specifically, the focus on inputs and outputs in a resource

---

[15] More specifically, biological populations can increase by births or immigration and can decrease by death or emigration. But theoretically closing a population to immigration and emigration conceptually simplifies how populations are regulated.

environment marked by scarcity, where strategic management is required to bring inputs/outputs and resources into equilibrium (Tucker & Hurl, 1992; Thompson, 1967).

Wulczyn (1996), moreover, notes that child welfare populations are made up of individual children and the experiences of those children are routinely modeled at the individual level.[16] Wulczyn continues by identifying that, while minute populations fluctuations are inextricably related to individual-level decision making, that it does not necessarily follow that population level dynamics are merely an aggregation of individual-level experiences. Dynamics that occur at the population level, therefore, are connected to individual-level processes but may also contain idiosyncratic mechanisms which are not mere aggregations of individual-level processes, but, instead, are forces which constrain at the population level. In other words, the dynamics of a child welfare population may produce a structure that bounds street-level work in ways that are non-obvious at the client or worker level and opaque to analyses conducted with individual-level data (see also Abbott, 2016).

Now that the general theoretical proposition of this dissertation has been summarized, this section will continue by defining key concepts and expanding upon the population ecology and social dynamics theory. This section continues by discussing individuals and populations and the differences between them, then moving on to consider time and change. The section concludes by presenting examples of dynamic populations in organizational ecology and epidemiology.

1.2.1 Population as Empirical Subject

In the Introduction, I introduced a working definition of "population" which relates to unique structure defined by its behavior related to its size and rate of change. In this section, I

[16] Wulczyn (1996) identifies an asymmetry between individual- and population-level research which takes place in the child welfare system. Since that writing, individual-level analysis continues to remain dominant in the child welfare literature.

elaborate that definition and contrast it with more commonly used determinative definitions. In some sense, a barrier to the conceptualization of "population" is the obviousness of the construct. In common usage, a "population" is a conceived of as collection of individuals. The grouping of individuals into a population is typically done by assigning temporal, geographic, and other unit-level characteristics to individuals, and then aggregating like individuals into populations. Broadly, this basic definition can apply to both biological and sociological populations (see Bottomore, 2010; Coulson & Godfrey, 2007). However, conceiving of a population as determined by the individuals which comprise it conceals as much as it reveals. Concealed in particular are the set of characteristics of a population which specify that population uniquely, but do not specify the individuals which comprise it, because "population" is a systems-level concept. Thus, the attributes of a population are not reducible to the attributes of single members of that population. Inversely, the characteristics of single members of the population do not aggregate into all of attributes of the population (Ariew, 2008; Goudge, 1955).

The population, then, is distinct from any aggregation of individuals, and takes on characteristics that are irreducible to traits of individual members (Ariew, 2008; Goudge, 1955). For the purposes of this dissertation, then, a child welfare population will be defined as a quantifiable subject whose numerical value is a function of a set of structural change processes unique to that population. As an example, the population of children in out-of-home care includes not only the number of placed children, but also unique information about the systematic processes through which children enter into and exit from care. By conceiving of a population as a set of unique structural characteristics, ways in which population can be defined as an empirical subject become clear. Population theory points to rates of change and capacity criteria as constructs which define the unique behavior of a given population, and holds the possibility of explaining differences in behavior across time and space. Thus, population theory is a structural theory, though not a wholly deterministic one. The application of the population change processes related to growth and capacity provide points of entry into how to understand the ability of populations to illustrate systems behavior focused on growth rate, capacity, and feedback (Coulson & Godfrey, 2007).

1.2.2 Change and Time

Goudge (1955) notes the temporal indeterminateness of the concept of biological population, noting that one of the key principles of population is change over time. The discussion of feedback process which shape entry and exit processes across time in the previous section presages the need to situate populations within a dynamic environment. In practice, child welfare decisions are embedded in dynamic environments (Lipsky, 2010). The process of change over time is also the subject of the sociological field of social dynamics, which focuses on the study of change in social systems.

Time and change have become important objects of study at the individual level with the application of survival and hazard models to describe the experiences of children in out-of-home care (Benedict & White, 1991; Courtney & Hook, 2012; Courtney & Wong, 1996; Courtney, 1995; Kemp & Bodonyi, 2002; Wulczyn, 1996; Wulczyn, Kogan, & Dilts, 2001). However, time and change models applied to child welfare populations are less common (Tucker, Hurl, & Ford, 1994; Tucker & Hurl, 1992). The recognition that time paths matter at the individual level, then, has not spread widely to population-level studies of change (Wulczyn, 1996; Tuma & Hannan, 1984).

Without pressing the analogy too far, there are similarities between individual-level instances where time and change matter and population-level instances where the same holds true (Abbott, 2016). An example of this is the event structuring of dynamic analysis. Events refer to some time-specific change in state for a variable of interest (Tuma & Hannan, 1984). An example of an event could be a child's entry into out-of-home care or exit from out-of-home care. For an individual child, this is a meaningful change in status and the trajectory of a child's spell within out-of-home care is of significant policy and practice interest (Courtney & Hook, 2012). Similarly, at the population level those same events have an effect—either the population in out-of-home care is increased or decreased by one at some point in time (Wulczyn, 1996). The unique temporal positioning of an event situates that event relative to other events that are happening across time. In the case of an individual child, this helps carve out the trajectory of a particular spell. Similarly, in the case of the population, time-ordered events allow a focus to be placed on the subsequent effect of a particular set of events, or an interrelationship between events over time. Dynamics, then, provide a particular way of looking at change, capacity, and feedback over time.

Wulczyn (1996) proposes study of change in child welfare populations based on time-event models. Chapter 2 will expand on that conceptual model.

1.2.3 Applications Using Dynamic Populations

Attempts to use biological populations as a metaphor for human systems have a long and spotty history (see Mayer, 1962; Penrose, 1934). Ecological concepts seem to have found their most robust use as applied to human-built systems, and have been usefully applied in urban, organizational, and population health (Krieger, 2011; Berry & Kasarada, 1977; Duncan, 1964). This part of the dissertation will focus on an illustrative description of the application of dynamic population theory in organizational ecology and in epidemiology.

1.2.3.1 Organizational Ecology

Organizational ecology provides an example of how the determinants and structure of populations dynamically interrelate in ways that describe the firm entry and exit in markets. The application of dynamic population processes in the sociology of organizations was the primary domain of Cornell University's Michael Hannan and John Freeman, and UC Berkley's Glenn Carroll. Hannan, Freeman, and Carroll used dynamic population processes to explain firms entry in to and exit out of markets, the growth and decline of a firm within in a market, and the capacity of a market to carry a certain number of firms. These studies made use of the concepts of population growth and capacity discussed earlier in this section—specifically entry and exit analogues and some capacity criterion—which allows an organization to adapt to the broader organizational environment (Hannan & Freeman, 1977).

Perhaps the most important explanatory concept in organizational ecology is carrying capacity. Carrying capacity is related to the concepts of entry in to and exit out of markets, and the growth or decline of firms, but is important to distinguish. Organizational ecology provides an ideal case to illustrate carrying capacity because of the relative simplicity of that concept within organizational populations—it is often as simple as considering the number of organizations within a given setting. Then the likelihood of openings and closings, as well as the growth rate of firms, can be explored relative to that organizational density.

The number of organizations in existence acts as a governor in multiple organizational settings. This means that as the total population of firms changes then the likelihood of a new firm starting is adjusted based on that total population. Similarly, the growth rate of firms adjusts according to the total population of firms. Carroll and Hannan (1989) observe that the history of firms in a number of different sectors follow a common pattern: initial entry of few firms, rapid expansion, decline, and stabilization. One tested explanation involves the broad carrying capacity for newspapers in a given setting. That is, there are some constrained latent factors (legitimation, readership, advertisers, labor force, cost of material/equipment, etc.) which may act to limit the growth of newspapers at a certain criterion number of newspapers in that setting—acting on both the founding and closing processes of newspapers in that area. Carroll and Hannan found patterning which related the founding and closing of newspapers to carrying capacity measures (see also Carroll & Huo, 1986). Though they were not able to directly observe the latent factors which created the resource constraints, the theoretically-predicted patterning provided evidence, not otherwise explained, for the carrying capacity model. They concluded that the criterion number of newspapers as a single independent variable could explain the growth and stability of the population of newspapers in a given setting.

The importance of capacity applied more broadly than to newspapers. For example, Barron, West, and Hannan (1994), examined the growth and decline of credit unions in New York City. A single criterion—number of credit unions in existence—was able to explain the founding rates and growth rates of such firms. More specifically, the founding rates and growth rates of credit unions shifted as the population size of credit unions changed. Hannan and Freeman (1987) found a capacity-based relationship between the number of labor unions in existence and the founding of additional labor unions over time. Nielson and Hannan (1977) found that resources and the availability of qualified candidates set the capacity criterion for the growth and contraction of educational systems in a multinational study over a period of time.

Organizational ecology has also been applied to problems within the child welfare system. The organizational ecology of foster homes has been the subject of an organizational ecology-type density study (Tucker and Hurl, 1992). This study suggested a density-dependent relationship between the number of existing foster homes and the entry of new foster homes into the population. (see also Tucker, Hurl, and Ford, 1994 (applying hazard models to a similar problem))

The organizational ecology literature illustrates several critical points. Primarily, it illustrates the applicability of dynamic population models to settings outside of animal populations and the ways that parameters—growth rate and capacity—operate in those settings. Conceptually, we can also see how the behavior of the population of organizations is distinct from the operation of any single firm or the decision-making process of any individual within a given firm.

1.2.3.2 Epidemiology

Population growth modelling is a cornerstone of epidemiological theory because it helps describe the speed and growth of contagion. Moreover, the application of population thinking within epidemiology employs the determinants and structures within contagion populations to craft interventions. Within the field of epidemiology, these transmission dynamics act on a fine-grained temporal scale to spread disease across populations and pose important public health planning questions related to the severity, extent, and duration of the disease (Brauer & Castillo-Chavez, 2012; Roux, 2004; Anderson & May, 1991). One interesting aspect of epidemiological modeling is that many disease models take place in short enough duration that some broader demographic changes that happen over longer time spans can be excluded from the model (Brauer & Castillo-Chavez, 2012). This is of importance to the consideration of child welfare systems because the effects that are captured in certain fine-grained time scales may speak to different outcomes of interest not captured well in longer-period analysis. Similar to organizational ecology, criterion-related questions about the density-dependence of rates of disease spread is of particular interest to epidemiology (Brauer & Castillo-Chavez, 2012; Getz & Pickering, 1983).

The simplest models of contagion spread are known as Kermack-McKendrick, or S-I, models, where the rate and extent of an infection is modeled based on numbers of susceptible individuals and infected individuals (iterations of the model also include recovered (susceptible again or not), quarantined, and deceased individuals). The populations of interest, susceptible infected individuals, are analyzed in concert with a rate parameter that specifies the reproduction of the disease. From this small number of variables several values of interest can be derived including the peak number of individuals in the population infected and the duration of the contagion (Brauer & Castillo-Chavez, 2012; Brauer, 2005). Consider the case of measles transmission. Patterning of measles outbreaks tends to be seasonal, but with variations over time in the extent of the contagion. This complex patterning has been shown to be governed by changes in susceptible populations (some of those changes brought about by vaccination) (Earn, et al., 2000). Earn, Rohani, Bolker, and Grenfell (2000) suggest that insight into the nonlinear dynamic coupling between the susceptible and infected populations provides guidance for the design of vaccination policy to reduce future outbreaks. Similarly, nonparametric empirical dynamical models have also been applied to the coupling of flu epidemics with climate conditions as a way of targeting interventions and marshalling resources (Deyle, et al., 2016).

Epidemiologic phenomena are studied as population-level dynamic systems where, again, the focus is placed on a relatively narrow number of parameters which can, in turn, lead to insights on overall population health. Similar thinking can be applied to child welfare populations and child welfare policy planning.

1.2.4 Conclusion

This chapter presents a theoretical underpinning for conceptualizing child welfare populations. Specifically, a child welfare population is conceived as an empirical subject which has properties that are irreducible to individuals within that population. In particular, those properties are the entries, exits, the rate of change, and the capacity of the population system. Importantly, theory suggests that population change itself is a particular dependent variable of interest that moves as a function of some relationship between rate, capacity, and entries/exits. This dissertation will apply these theories to entries and exits in out-of-home care and to case openings and closings in dependency court.

1.3 Research Question

This chapter summarizes a theoretical perspective to examine population change premised on the idea that the systems structure exists in child welfare. The guiding research question for the remainder of this dissertation is: By empirically observing the dynamics of child welfare populations over time, can we infer the existence of systems structures that shape the temporally-ordered behavior of those populations?

In other words, this dissertation applies theory and methodology to see if we can observe the existence of resource constraints within every day entries and exits in the child welfare system. Though I do not identify the constraints themselves, I seek to identify the effect of the constraints on child welfare populations. The theory described in Chapter 2 guides this question by illuminating ways in which we might observe these constraints in a dynamic system.

Chapter 2:
Heuristic

This chapter represents an effort to join demographic, sociological, and ecological theory in application to the question of how systems structures shape populations in child welfare. The theoretical underpinnings of this dissertation are operationalized through the hypothesized existence of some system of dynamic population-level mathematical equations which describe child welfare populations and identify determinants of time-series behavior. An illustrative conceptual model of such a system is as follows, to-wit:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r'[\pi' x(t) - y(t)]$$

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = r''[\pi'' y(t) - x(t)]$$

where the entries, y, into and exits, x, from child welfare systems[1] are defined by the function's dynamic, interrelated population processes which are driven by negative feedback and partial adjustment loops. These processes are governed by rate, r, and capacity, π, parameters.

Where present, the processes described in the conceptual model shape child welfare populations and may impact the ability of individual-level decision makers to base their decisions solely on subjective evidence from the case in front of them, instead suggesting that population-level forces routinely place constraints on those decisions.[2] For example, one way that might manifest itself in practice is though limits in the number of new cases that can be processed in a given time period or in the number of foster homes available to place children. So

[1] To make the description less cumbersome the models are simplified through this chapter to focus on out-of-home care systems (except where noted), with *y* representing out-of-home care entries and *x* representing out-of-home care exits. As a conceptual matter, however, both the *x* term and the *y* term could represent entries or exits in out-of-home care, or openings or closings in dependency court systems. Section 4.1.2, *infra*, contains a more complete description of the variable terms which can be included in this theoretical model.

[2] The alternative, specifically independent, discrete case-level decision making, is discussed in Part 2.1.4, *infra*.

even if there is additional need, system structures may bound the ability of child welfare to react to that additional need. Evidence of these systems structures highlights the importance of the treatment of child welfare caseloads as populations (Abbott, 2016; Wulczyn, 1996; Emerson, 1983).

Part 1 of this chapter describes this system of equations in detail, and provides a brief discussion of the parametric and nonparametric analysis of the system. Part 2 of this chapter reviews the child welfare and court systems literature for indications that resource constraints and feedback loops may provide some explanation for system behavior. This chapter concludes, in Part 3, by stating the motivating questions of this analysis.

2.1 Heuristic Model

Described in the sections that follow is a mathematical model for analyzing the way that populations in child welfare systems change based upon factors that occur at the population level. I frame this mathematical model as a heuristic. Heuristics are devices to assist in the conceptualization of problems by providing a way of thinking, and within those ways of thinking providing lines of understanding about useful ways to solve problems as opposed to useless ways. Heuristics, then, are theories of how to find things out (Abbott, 2004). In this case, the population frame provides a new dimension of analysis for child welfare research. However, the mathematical model laid out in this chapter does not so much act as a solution to population questions in child welfare, instead serving broadly as a way of thinking about those questions that can illuminate pathways to finding those solutions.

This part elaborates the theoretical model. In the first parts (2.1.1 through 2.1.3) the model as described is parametric, but the intent of this discussion is to additionally use the model as a heuristic to identify theoretical relationships within child welfare populations and mechanisms which may structure those relationships.[3] It is important, then, that this section serve as a guide to a way of thinking about populations that emphasizes change, time, system, feedback, and capacity (Abbott, 2016; Wulczyn, 1996).

2.1.1 Model of Change in an Endogenous System

Change in population systems always presents the current state of the system in terms of previous states (Abbott, 2016; Tuma & Hannan, 1984). In population systems that change can be modeled as a function. In the most general case, the change in population size can be described by a continuous function:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = F(y, (\ t)) \tag{2.1a}$$

where some unknown function of y over time (t) describes the dynamical relationship that leads to increase or decrease of the population or population subpart in that unit of time. The population size itself can, likewise, be defined as a function:

$$y_t = F(y_{t-1}, t) \tag{2.1b}$$

where some unknown function of y_{t-1} and t describes the dynamical relationship between y_t and a previous state of y during a fixed increment of time. In other words, the general idea is that the entries into out-of-home care we are observing now are related, in a coupled way, to entries that we observed at a previous time. That is, that by understanding how many entries may have occurred previously we can make some reliable predictions about the entries that we are observing at present. The specification of $F(y, t)$ illustrates critical relationships which underlie the dynamic processes.

Tuma and Hannan (1984) consider the following model as one way to think about the process of continuous change in social system:

[3] The existence of those theorized relationships becomes critical as nonparametric modeling is discussed in Part 2.1.5.

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r[y^*(t) - y(t)] \quad (2.2a)$$

where r is the rate adjustment of the value of y to its target value of y^* over some time (t). The y^* term describes a criterion, defined more completely *infra*, to which the system is continuously adjusting at rate r over increments of time given the amount of y in the system. For example, if you consider a system with a single resource constraint, we can think of the y^* term as describing the number of entries possible given the available out-of-home care beds or the number of exits possible given the amount of time required to process exits. Thus, the change in y over time t is a function of that speed of adjustment in relation to the goal state of the system. For example, this model predicts that observed entries in the past relate to present observed entries in a predictable way, structured by some rate of change and some criterion number of entries. This model is referred to as a linear partial adjustment model. Equation 2.2 can also be rendered in a discrete form as a linear difference equation:

$$\Delta y_t = r[y_t^* - y_{t-1}] \quad (2.2b)$$

The most notable difference between the continuous form and the discrete form is that the continuous form gives a value for change in y over the infinitesimal time increment (t) whereas the discrete form gives the value of y_t. The expansion of Equation 2.1a in the parts that follow the continuous form of these models will be reported and described, however, the reader should consider the discrete form as a potential alternative for the functional relationship between the variables.[4]

[4] In practice terms, it is probably most useful to conceptualize these processes as continuous processes of feedback and change in response to that feedback and capacity. Thus, as a conceptual model, these processes can be thought of as acting minute-to-minute in the practice environment. However, from a practical research standpoint, it becomes necessary to render these processes as discrete in cases where continuous functions may be unsolvable or where limitations in data sources force discrete analysis.

2.1.1.1 Rate of Change and Equilibrium

Tuma and Hannan (1984) describe the sociological value of both the r and $y^*(t)$ components of this model. The adjustment rate, r, contains information about institutional constraints which bound system responsiveness. Larger values of r indicate quick adjustments over the time period, whereas smaller values indicate slower adjustments. The speed of adjustment relates to institutional constraints which may include things like formal policy structures (including complexity and density of those structures), informal institutional goals, and costs of change to those policy or rule structures. The adjustment rate is an indicator of institutional forces which act to promote efficiency in times of stability and serve as a limiting force in times of rapid change.

The criterion value, $y^*(t)$, however, requires more complex treatment. It can be viewed as a point of equilibrium.[5] An equilibrium point represents the value at which forces within a system are balanced either as a steady state or as a critical point. Tuma and Hannan (1984) describe $y^*(t)$ as a criterion of carrying capacity[6]—a population biology construct used to define the number of individuals an environment is able to sustain. The fact that an equilibrium point exists says nothing about whether or not the system sits at point or continually circles around it. Equilibrium points can also manifest themselves as point attractors which drive the motion of the dynamics of a system. The existence and stability of an equilibrium point is a critical empirical question. In fact, understanding whether the system being studied exists persistently at equilibrium or if exists predominately out of equilibrium is an essential methodological question,

---

[5]If an equilibrium exists, then $y^*(t)$ can be thought of as the equilibrium point of y (Tuma and Hannan, 1984). But as a general matter, and for systems where there is no known equilibrium, y^*should not be thought of simply as the equilibrium point of y value, but of the broader system (see Hannan, 1978). This may have the practical consequence of rendering y^* unobservable.

[6] The convention of describing $y^*(t)$ as "carrying capacity" is adopted throughout this dissertation.

because systems at equilibrium can be studied effectively using cross sectional methods whereas systems out of equilibrium necessitate dynamic analysis.

To reduce the uncertainty around the conceptualization of $y^*(t)$ as an equilibrium point, Tuma and Hannan (1984) describe it "as the level toward which causal forces are impelling y" (p. 339). While $y^*(t)$ could be a fixed value inherent to the system, it is more likely that it ebbs and flows across time. This pliability of $y^*(t)$ is important to Abbott's (2016) critique of equilibrium as a fixed value. Alternatively, it can be thought of as a property of "the interaction of the structure with a particular environment" (Hannan, 1978, p. 14). Hannan further describes potential interpretations of $y^*(t)$ as organizational goal or objective, or as the "utility maximizing level of y given preferences and objective constraints" (p. 15). Tuma and Hannan (1984) note that $y^*(t)$ can be the product of purposeful decision making and an emergent property of uncoordinated social forces.

In the case of child welfare, it is likely that $y^*(t)$ represents both a purposive institutional system coupled with some degree of emergent behavior. An example of a purposive institutional system would be a capacity designed to address a certain rate of child maltreatment. An emergent behavior might be a criterion number of entries set by the amount of time that child welfare workers have available to them in their practice. Critical, then, to the practical significance of including $y^*(t)$ in this theoretical model is the idea that behavior by actors in the system will attempt to adjust the behavior of the system to align the values of $y^*(t)$ and y, and that there is some tension between the actual state of the system and the goal state of the system.

2.1.1.2 Single-Variable Change in the Child Welfare Context

Before elaborating this model further, it is useful to pause briefly to contextualize it in its simplest terms. Wulczyn (1996), drawing from the continuous form in Equation 2.2a, argues that

$\frac{\mathrm{d}y(t)}{\mathrm{d}t}$ can represent the change in the out-of-home care caseload as an absolute measure in the time increment (t). In this case, the $y^*(t)$ term can be thought of as some criterion population size, where y represents the out-of-home care population at a time (t). In this conception, then, $y^*(t)$ can be viewed as a practical or policy-driven carrying capacity which describes the practical or preferred limit to the number of children in out-of-home care over a given time. I would like to take a slightly different tack, rendering the y value not as absolute population size, but as a component of that population size—for example, instead of looking at the total number of children in out-of-home care, I look at the entries into and exits from out-of-home care. The partial-adjustment model, as described by Wulczyn, is not only useful exclusively to conceptualize the change in the absolute number of children in out-of-home care, but also at the change in the components (i.e. out-of-home care entries and exits) which drive that absolute population size. Another way to think about this is that it is the entries and exits over time which define the population size. More specifically, we can think of y as representing the number of children entering or exiting the out-of-home care subsystem or child maltreatment cases opening or closing in the court subsystem. For the purpose of the example in this part, let us focus on out-of-home care.

Where y represents entries into out of home care, $\frac{\mathrm{d}y(t)}{\mathrm{d}t}$ is defined as the change in the number of entries along a continuous curve. Here the $y^*(t)$ can be viewed in terms of the carrying capacity describing the practical or preferred limit to the number of children entering out-of-home care over a given time period. The $y^*(t)$ term, then, can be conceptualized as a broad ideal capacity measure where the system is either (1) responsive to that criterion volume of entries alone, or (2) that criterion number of entries as an indicator of structural realities contained within the system.[7] Examples of structural realities which might impact the capacity at which a system can absorb new entries might include an organizational/policy structure or resource dimension, governed by policy, practice, or organizational structures, which may include financial resources within the system, workers and worker time, resources related to administrative support for placement, and existence of available placements.[8]

If the number of entries, y, rises above that criterion, we would expect to see fewer entries in some future state of the system; and conversely if the number of entries, y, falls below that criterion, we would expect to see more entries in some future state of the system. Thus, at the population level, the behavior of the system is not solely dependent on case-level decisions, but also on the existence of criterion measure which impels the behavior of the system based on fluctuations at the population level (Wulczyn, 1996). If such a criterion capacity measure exists and the out-of-home care system behaves in response to it, then we would expect to see systematic evidence of that capacity measure within out-of-home care time series data.

2.1.2 Model of Change with Multiple Variables

Equation 2.2 contains two parameters, the rate of adjustment and the criterion, internal to the relationship of y to itself. A further iteration of population systems is in considering the effect that an external, exogenous[9] parameter may have on that time series. This iteration of the model brings us to the central questions in this dissertation: Are different components of the ways that child welfare populations grow and shrink related to each other across time? Thus, for example, instead of asking whether out-of-home care entries are related to themselves across

---

[7] See Section 2.1.5 discussing potential weaknesses in causal arguments in nonparametric population analysis (Cobey and Baskerville, 2016).
[8] See Section 2.2.1 for an elaboration of potential resource constraints within the child welfare system.
[9] Here "exogenous" is meant to describe a time series parameter with characteristics that are different than those of the series described by y. As we will see, these exogenous parameters are not "exogenous variables" in the sense that their value is independent from the states of other variables in the system.

time, I am now modelling whether out-of-home care entries are related to out-of-home exits. In order to do this, however, I need to redefine the criterion term to capture constraints that exert forces on both variables at the same time. Imagine, for example, a system that is just limited by the number of available placements. In that case, entries may be sensitive to that criterion, exits may be sensitive to that criterion, and the influence that entries have on exits may be sensitive to that criterion. Thus, it is important to describe the term $y^*(t)$ in a way that captures that criterion in the context of both entry processes and exit processes. Following Tuma and Hannan (1984), the term $y^*(t)$ can be redefined in order to include the influence of exogenous variables change over time as $y^*(t) \equiv \pi' x(t)$, where $x(t)$ is the exogenous variable changing over time. If we think of y as out-of-home care entries, then we can think of x as out-of-home care exits, for example, and the π' term contains, in part, some adjustment factor that relates $y(t)$ to $x(t)$, along with some information about the system's preferred target value (similar to $y^*(t)$). In the expanded equation:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r[\pi' x(t) - y(t)] = r\pi' x(t) - ry(t) \tag{2.3}$$

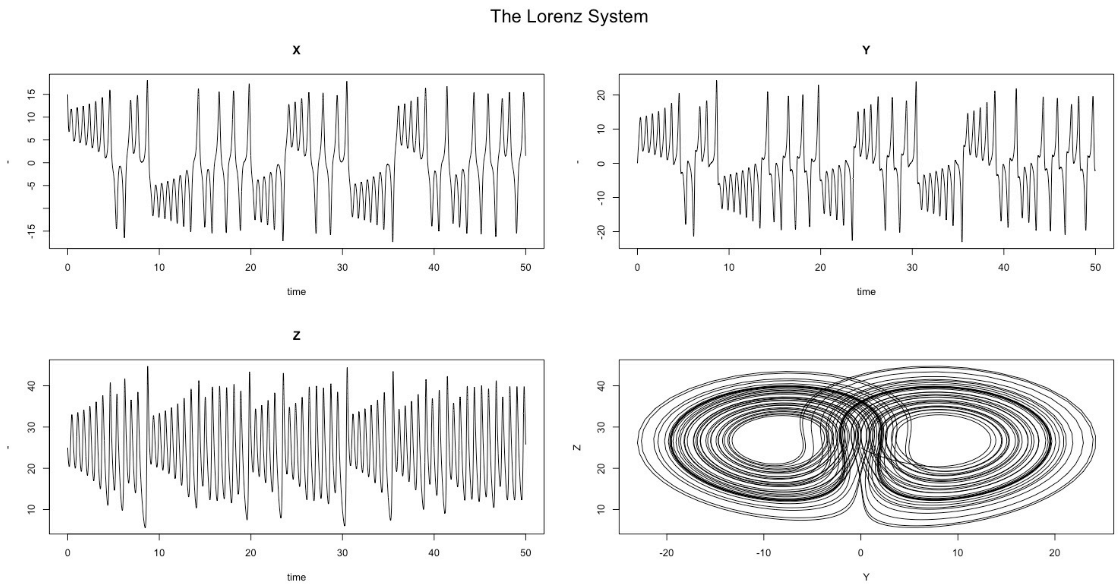
then, in addition to the information about partial adjustment processes (through the $r\pi' x(t)$ term) described above, this model contains key elements of regulated negative feedback loops (within the $-ry(t)$ term). It remains possible that $\pi' x(t)$ alone does not entirely disentangle the components which set the criterion value of $y^*(t)$, and that it, too, serves as an indicator of underlying processes. In spite of the possibility of masked collinear variables acting as the real causal drivers, Equation 2.3 illustrates a feedback- and adjustment-governed relationship between $y(t)$ and $x(t)$.

Continuing our earlier example where y represents out-of-home care entries, let us assume that x represents out-of-home care exits. Equation 2.3 can be read as the change during time (t) in the number of out-of-home care entries, y, is a function of the rate of adjustment, r, on the difference between the number of out-of-home care exits, x, adjusted by a criterion parameter, π', and the number of out-of-home care entries, y. Thus, Equation 2.3 places some dependency of out-of-home care entries on the number of contemporaneous out-of-home care exits. In addition to the previously discussed insights provided by the rate of adjustment and criterion terms, Equation 2.3 models a population system where the actions of entry and exit are connected. This impacts the $y^*(t)$ from Equation 2.2 by explicitly stating that one of the structural realities in the out-of-home care system is that relationship between entries and exits. And as with $y^*(t)$ in Equation 2.2, the $\pi' x(t)$ term either serves as an independent criterion, or as criterion indicator of other structural drivers in the system. Thus, the magnitude of the π' relationship may suggest directions for exploring what other structural realities make up the remainder of the impelling force—for example, if there is a highly correlated relationship between entries and exits that may indicate that capacity of workers and availability of placements are more significant driving forces than the underlying need for out-of-home care services or the capacity of intake workers.

2.1.3 Model of Change in a Coupled Dynamic System

As a final iteration of our model, we synthesize Equation 2.3 into a coupled system of interacting, dynamic equations. Before returning to the subject of this dissertation, I would like to illustrate the dynamics of a system of differential equations. Let us momentarily consider a famous and well-defined traceable chaotic system of equations: the Lorenz System (Lorenz, 1963). The Lorenz System is used to describe the turbulent behavior of fluids in atmospheric

Figure 2.1—The Lorenz System.



An illustration of three time series: x, y, and z, and a state space graph of the position of y relative to z with the trace following the time dimension. The parameter values for this model are $\sigma = 10$, $r = 28$, and $b = \frac{8}{3}$ over 50 units of t in .01 increments of t. This graphic was produced using the R package deSolve. (Soetaert, Petzoldt, and Setzer, 2010).

convection, but is chosen here as an illustration for its simplicity, aesthetics, and renown. The system is produced by three equations:

$$\begin{aligned} \frac{\mathrm{d}x(t)}{\mathrm{d}t} &= \sigma(x - y) \\ \frac{\mathrm{d}y(t)}{\mathrm{d}t} &= rx - y - rz \\ \frac{\mathrm{d}z(t)}{\mathrm{d}t} &= xy - bz \end{aligned} \tag{2.4}$$

where the typical parameter values are given as $\sigma = 10$, $r = 28$, and $b = \frac{8}{3}$.[10] Figure 2.1 presents plots of the individual time series for x, y, and z, as well as a state-space attractor reconstruction of the overall system. The plot of the attractor represents the position of y relative

[10] The structure of the attractor changes considerably with different parameter values, producing point solutions or independent lobes with no equilibrium point.

to z, with the trace connecting those relative positions through time. The shape of the plotted Lorenz system is commonly referred to as a "butterfly attractor." As with our partial adjustment model, the Lorenz system is defined by interrelated variable systems—x is dependent on states of y; y is dependent on states of x and z; and z is dependent on states of y. Each variable subsystem contains its own adjustment parameter (σ, r, and b). The orbiting traces around the lobes in *Figure 2.1* are governed by attractors, with the left/right shape being driven by an unstable equilibrium point at the origin of y. The aesthetic appeal of the Lorenz attractor underlines the patterned ordering of a chaotic system, but also serves to visualize the theoretic potential of a system governed by equilibria and attractors. The traces of the time series across time form into predictable orbits around the unstable equilibria of the two lobed attractors. Thus, even in such a high-variability, unstable system, it is possible to understand things about system behavior—such as interrelated processes, equilibria, and system feedback—in those conditions. The Lorenz system example is provided at this point for illustrative purposes before we move into a discussion of the coupled form of Equation 2.3.

If a system of equations exists in the linear, non-chaotic context, we find that equilibriums take point solutions. An example of this is the simple linear demand curve in economics where the equilibrium is the intersection point or points of the demand curve (quantity demanded by price per unit) and the supply curve (quantity produced by price per unit). Similarly, some biological populations can be modeled as linear births and deaths with the intersection indicating the equilibrium point (defined as carrying capacity). The equilibrium points for both simple demand curves and simple population models suggest regulating feedback which returns the models to that point depending on the unit production/sales or on the number of individuals in the population. These notions of feedback become more explicit when demand curves and populations are modeled in dynamic forms, using either difference or differential equations as well.

Then, in our final deterministic iteration of Equation 2.2, two paired forms of Equation 2.3 can be expanded to a system which serves as a conceptual model for this dissertation:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r'\pi' x(t) - r' y(t) \tag{2.5}$$

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = r''\pi'' y(t) - r'' x(t)$$

where the terms are similar to Equation 2.3, recognizing that in the change in y subsystem that the r and π' parameters may be different than in the change in x subsystem (Tuma and Hannan, 1984). Importantly, Equation 2.5 recognizes the simultaneous occurrence of y and x, and the simultaneous effect that the variables have on each other. In the case where y is out-of-home care entries and x is out-of-home care exits, the system of equations described in Equation 2.5 provide a model of population growth where the total population size is a product of the difference between those entries and those exits, and where entry dynamics are affected by exit dynamics and vice versa.

The critical theoretical principles illuminated by Equation 2.5 are as follows, to-wit:

1) The coupling of the equations;
2) The existence of a criterion carrying capacity parameter;
3) The feedback systems within the coupled equations; and
4) The dynamic nature of the coupling, carrying capacity, and adjustments.

2.1.4 Randomness as Empirical Concept

Though Parts 2.1.1 through 2.1.3. describe deterministic functions, it is additionally a possibility that the functional relationship could include stochastic features (see Tuma and

Hannan, 1984). Indeed, stochastic processes provide an essential alternative, or addition, to the deterministic forms described above. This part will proceed by describing randomness in time series and then conclude by contextualizing the role of randomness in this analysis.

Consider that

> [a]t the most basic level, we say that an event is random if there is no way to predict its occurrence with certainty. Likewise, a random process is one for which we are not able to predict what happens next. That is, what we have in mind when we call the behavior of a dynamical system 'random' is our inability to predict its future behavior, and any definition of randomness we employ in this context must somehow do justice to this intuition.

(Frigg, 2004). Following that definition, let us imagine a census set of real integers containing all of the observed sums of y_t, aggregate entries into out-of-home care for a given population in a given time period: $\mathbb{Z} \equiv \{0 < y_t < m\}$, where m represents the maximum observed sum.[11] Let us further imagine that these observed sums follow some definable distribution, $\mathbb{P}\{y, t\}$, where the observation of a particular integer has a defined likelihood. Thus, for a given y_t, the probability of a certain number of aggregate entries would be along that probability distribution. Similarly, for a time series, $y = \{y_t; t \in T\}$, the probability of a certain number of aggregate entries for each y_t would be along that probably distribution and independent of any previous value of y_{t-n}. Conceptually, then, in a random time series any given value of y is equally likely to occur at one time t as it is at any other time t, or, drawing from Equation 2.1b:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = F(y, t) = \mathbb{P}[\{y, t\}] \tag{2.6}$$

Equation 2.6, then could be described as a true random process.

[11] It is possible to consider all *possible* sums of aggregate entries—a number bounded by the population size—however that would meaningfully depart from reality and practical possibility, and, approaching the upper bounds, frustrate the mathematics.

An alternative conception of randomness could contain some central measure that is circled by a random process (Tuma and Hannan, 1984; see also Simpson, et al., 2000 (discussing maltreatment incidence rates in child welfare administrative data)). For example, the change in the number of out-of-home care entries, $[y^*(t) - y(t)]$, could be distributed around some mean value of entries in a Gaussian process. Equation 2.7, which follows, describes that mean as $y^*(t)$—our criterion parameter from Equation 2.2—and the Gaussian process as $F_g(t)$:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = [y^*(t) - y(t)] + F_g(t) \tag{2.7}$$

Within a Gaussian process, the mean of the distribution is zero, and the probability distribution of the function is normal around zero under the constraints of standard deviations. As another example, standard Brownian motion—a random process with a mean of zero and a deviation which is coupled to time—could be appended a central state of the time series in this form:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = [y^*(t) - y(t)] + F_W(t) \tag{2.8}$$

where $y^*(t)$ is again a mean–based criterion of y, and $F_W(t)$ represents the standard Brownian process[12], or the random walk. Though the standard Brownian process is built around the Gaussian distribution, its innovation is that it does not have a "memory"—creating predictable persistent or anti-persistent states—and thus has no serial correlation between adjacent time increments moving it more closely toward the true random process previously described (Hastings, et al., 1982).

Though the realm of stochastic differential equations is beyond the scope of this dissertation, I wish to reflect on Equations 2.6, 2.7, and 2.8 to make a substantive point about the nature of child welfare time series. In some sense, child maltreatment and state interventions into

[12] The standard Brownian process is probably more specifically referred to as the Wiener process.

that maltreatment as indicated within time series data should be random processes. In a technical sense, what I mean here is that at the population level, individual incidents of child maltreatment should be uncorrelated across continuous time or fine-grained discrete time periods.[13] Or, if not wholly uncoupled, then any coupling should be related to the latent baseline incidence of child maltreatment. Thus, Equation 2.6 presents an alternative model for an uncoupled time series, and Equations 2.7 and 2.8 present models for uncoupled variation circling around some latent measure of incidence. These conclusory statements flow from Abbot's (2016) time-dependent process view of social phenomena and Emerson's (1983) critique of single-case analysis of social system decision making. Emerson states:

> [t]he individual case provides an adequate unit of analysis only if social control agents themselves examine and dispose of cases as discrete units, treating each on its own merits independently of the properties and organizational implications of other cases[]

(p. 425). The treatment of each case as a "discrete unit[]," solely "on its merits," and "independently" should manifest itself in a time series in some form of randomness. Alternatively, if there is coupling and patterning within the time series then the independence of each case must be questioned, and that coupling and patterning must be explained.

In this sense, then, some type of randomness—whether true random or randomness circling a central latent incidence rate—is the expected form of the child welfare time series. When we are unable to predict the future state of the out-of-home care system given the current state of that system it provides some evidence that child welfare professionals are exercising their full range of professional discretion to adjudge, on its merits, the case in front of them as an independent, discrete unit. Conversely, the lack of randomness is suggestive of some systematic

---

[13] This is not to say that incidents of child maltreatment are not related to macro patterns such as the rise and fall of the economy or social programs (Berger, 2004; Krugman, et al., 1986), the seasonality of school calendars (Almedia, et al., 2017 (studying the Portuguese case); Carbone-Lopez & Lauritsen, 2013 (seasonality of youth victimization)), and other community-level features (Coulton, et al., 2007)—simply that entries should be unrelated to entries; exits to exits; entries to exits; and exits to entries.

structure that truncates professional discretion based on systemic pressures related to populations. This alternative was the subject of the discussion in Parts 2.1.1 through 2.1.3.

2.1.5 Weaknesses in Parametric Modeling and Nonparametric Alternatives

The model proposed in Equation 2.5 serves as a heuristic to describe theoretical relationships in a constrained, coupled system governed by population-sensitive feedback loops. Unfortunately, Equation 2.5 is but one example of a vast class of population equations designed to capture those features of a population. In a system with unknown population dynamics a priori model specification, then, presents challenges, as does the parameterization of a model selected a priori. Fortunately, there exist several nonparametric alternatives which can identify, by behavior of a time series, the existence of coupling of interest across time. Thus, even if a model cannot be specified, it is possible to infer from time series behavior the existence of constraints, coupling, and feedback processes. These nonparametric methods take the basic approach of positing that if a past value of a variable predicts a present value of either that variable or another variable, then time delayed reconstruction will be sufficient to glean information about the time series and predict future states (see, e.g., Takens, 1981; Granger, 1969). Of particular interest here is Empirical Dynamical Modelling (hereafter “EDM”), discussed more fully in Chapter 5, which detects interactions between coupled variables in nonlinear dynamical systems, and purports to differentiate directionality of the dynamic processes (Sugihara, et al., 2012). Thus, even in conditions where a parametric model cannot be determined a priori, there exist nonparametric tools which capture some of the predicted behavior of a dynamic system governed by interrelated processes such as negative feedback and partial adjustment loops.

2.2 Constraints and Feedback in Child Welfare

Why should we expect to see interrelated dynamic population processes driven by negative feedback and partial adjustment loops in the child welfare system? The following two sections describe related literature on systems constrains and systems effects first in the out-of-home care subsystem and then in the child welfare court subsystem. This section concludes with a brief synthesis of the literature.

2.2.1 Potential Explanations for Dynamic Behavior and Rate and Criterion Parameters in Child Welfare Systems

The complex ecology of the child welfare system described in past research indicates a number of constrained resources which could serve to explain the existence of a population carrying capacity. The complex ecology of the child welfare system described in past research indicates a number of ways in which the system may respond to the y^* or π capacity constraint terms. In addition to the in-flow and out-flow of children as they move through the system, structures that exist within organizations and policy environments act to shape the behavior of an ecological system. The child welfare system is also sensitive to resource constraints acting through six main interrelated and overlapping sources: monetary capital, human capital, bureaucratic capital, temporal capital, physical capital, and permanency capital. The availability, or unavailability, of those resources may alter the overall capacity of the system, manifesting itself in the entries into and exits out of the system by children. An alternative explanation to the present resource constraints is a rule-based approach to constraints. This section begins by describing the rule-based approach to constrained action. What follows then is a brief, abstracted description of those sources and examples of their component parts.

One way to differentiate among organizational ecologies is by identifying the formal rules of operation which govern constituents of that ecology (Hannan & Freeman, 1977). But these formal rules of operation with in an ecology may not simply act as type-specifiers, but operate as the motivators (even organizing principles) of organizational behavior (Stinchcombe, 1997). What this may look like in terms of fluctuations in populations based on organized rules is the obedience of child welfare workers to statutory law and bureaucratic or organizational policy. Moreover, broader rule and policy environments—including public policy environments—also act to shape possibilities within an ecology (Stinchcombe, 1965). Rule-based behavior is particularly important in the child welfare setting—both in dependency court and out-of-home care—because of the procedural and supervisory formalism which is required of child welfare practice. Take, for example, the supervisory relationship between caseworkers managing out-of-home placements and the dependency court system which oversees the conduct of that case. The legal, organizational, and informal rules which exist in that relationship are complex and salient in child welfare practice (see Lens, et al., 2016; Smith & Donovan, 2003). Similarly, accountability structures at the organizational level may also act as "target values" (the y^* or π terms, described above) which child welfare is continually adjusting to. The ordering of organizations around sets of rules provides a contrast to the more resource/competition-focused ecological approach, indeed this conceptual difference is a fault line amongst institutional scholars (see Stinchcombe, 1997). It is possible that these rules of operation could he conceptualized as part of the resource ecology which is described below (Lipsky, 2010; Brodkin, 2011; Brodkin, 2008). More specifically, the operational rule environment can help shape ways that street-level workers balance the resources and the demands in their practice (Brodkin, 2006).

While I wanted to acknowledge the theory which undergirds a rule-based analysis, this dissertation instead follows the more resource-focused approach of Hannan & Freeman.

An ever-present resource constraint in the child welfare system is public funding (Scarcella, 2004). For example, if budgets act to constrain child welfare populations then population sizes closer to that budgetary limit should be more inelastic than smaller populations. Limitations on federal, state, and local funds constrain certain kinds of child welfare activities, while subsidizing others (Scarcella, 2006; Courtney, 1998). Money is related to the human capital that is available in the system through personnel such as caseworkers, supervisors, lawyers, judges, and court administrators, and through outside service providers, and relative and non-relative foster parents. The child welfare workforce is often seen as a resource constraint (Smith & Donovan, 2003; Alwon & Reitz, 2000). Within the terms of these models, if the system is limited by the number of people available to perform tasks then there is pressure on the system not to exceed the number of tasks that the system can perform. Additionally, families bring their own human capital into the system (Paxon & Waldfogel, 2003).

Bureaucratic capital is conceptualized as the reports, petitions, and other paperwork that initiates cases and marks the progress of cases. Paperwork strain on child welfare caseworkers is well documented, suggesting that bureaucratic capital requires its own analytic category (Ellett, et al., 2007).

Related to monetary capital, human capital, and bureaucratic capital is temporal capital: the available time to get things done. For example, think about the ways that incentives shift in times where there is not enough time in the day to accomplish everything that needs to be accomplish, especially when compared to light work days. Multiplied across the entire system, how does time act to govern the work that does and does not get done? Though it cuts across many of these categories, temporal capital demands its own category because of some hard constraints that are placed on the timing of cases through federal and state policy, and through the reality of having to interact with a fixed court calendar (Lopez & Zuniga, 2014). Physical capital relates to the actual physical resources that are used within the system, from court rooms to agency offices to foster homes (see Wulczyn, 1996).

Finally, the child welfare system has a number of cross-cutting resources and incentives that are available to it designed to bring children out of out-of-home care and into permanent placements. I refer to those resources, incentives, and barriers as 'permanency capital.' In a general sense, permanency capital can be thought of in two distinct ways: First, as a set of resources that promote the movement of children from out-of-home care and into a permanent placement. Second, as a set of barriers which prevent that movement of children. Those concepts will be discussed in turn. Permanency for a child relieves the state and the agency of case management and some economic burdens[14] (Barth, 1997). More concretely, however, there are financial incentives available to families who provide children in out-of-home care with permanency (see Hansen and Hansen, 2005); to young adults moving toward a permanency goal of independence (Massinga & Pecora, 2004); and to the state and its agencies for ensuring timely permanency (Testa, 2004). Additionally, there is some policy pressure on workers, agencies, and courts to achieve timely permanency, which may have some effect on back-end case planning (Barth, Wulczyn, & Crea, 2004–2005). There is a broad body of literature on barriers to permanency in the child welfare system that include child factors (Olsen, 1982), family factors (Smith, Rudolph, & Swords, 2002), resource factors (Testa, 2004), worker competence (Albers,

[14] Or, at the least, shifting those burdens away from the day-to-day direct involvement of the child welfare system.

et al., 1993), system resources (Outley, 2006), availability of permanent homes (Hansen & Hansen, 2005), and many other factors.

These six categories of resource constraints suggest potential process explanations if systems behavior is observed in child welfare time series. However, the predicate of such analysis requires the determination that there are identifiable coupled dynamic processes in child welfare time series. Section 2.1 describes ways in which dynamic coupling can be derived from the behavior of case opening and closing processes. Behavior suggestive of dynamic coupling, feedback loops, and capacity constraints has been found in state-level aggregate out-of-home care entries and exits (Wulczyn & Halloran, 2017), and within a subset of the out-of-home care population, congregate care (Wulczyn & Halloran, 2018). The ability to infer capacity constraints and coupled relationships becomes increasingly important as analysis is done at fine time scales where available data for any of the six categories of resource constraints described above is limited, if available at all. At least one study, however, has found in linear models that out-of-home care entries and exits are not mutually predictive, even within context (Grogan-Kaylor, 2000).

2.2.2 Feedback and Context in Court Systems

If there is a bias toward the perception atomistic case review in the child welfare system, then that perception is strongly amplified in the court system where underlying assumptions about the objective analysis of a single case is one of the cornerstones of our judicial ideology—blindfolded justice, balancing the scales of truth. Resnick (1982) recognized that workload pressures impact the management of procedure, effectively situating individual cases within broader caseload streams. This line of research into caseload pressures suggested that judges (and court systems) were actively pursuing tactics to speed resolutions of cases, ration judicial work, and to reduce their overall caseloads (see, e.g., Purcell, 2003; Lippencott & Stoker, 1993; and Robel, 1990). Put bluntly by a respondent to a survey about caseload pressures, one judge responded, "I am forced to choose between a full study of the issues presented and a prompt disposition of those issues" (Robel, 1990, p.9).[15] Another judge described more attention paid to serious cases in conditions of extreme caseload pressure (Robel 1990). There is also evidence that shifting burdens of case processing at one point in a system can lead to "bulges" in other parts of the system—suggesting the existence of some broad system equilibrium state (Lippencott & Stoker, 1993). These mainly qualitative studies focus on case management in the Federal Court system, but serve to identify some judicial sensitivity to caseload. Similarly, several systems dynamics studies have reinforced the idea that judicial decision making is sensitive to time and caseload pressures—with judges more routinely dropping cases in times of intense caseload pressure (Lopez & Zuniga, 2014; Lopez & Porfino, 2009; Lancing, 2001). These systems dynamics studies were done in the state court and international context, suggesting that Resnick's observations apply beyond the Federal Courts.

More recently, a series of studies on judicial decisionmaking have used econometric time series methods to contextualize judicial decisions within broader factors (Leibovitch, 2017; DePew, et al., 2016; Eren & Mocan, 2016; Leibovitch, 2016). Libovitch (2017) quantifies the relativeness of legal judgment in criminal courts, suggesting that particular judicial decisions are made in the context of other judicial decisions which are being made around the same time and in the same place. For example, sentence-length distributions varied by county. Additionally, judges who were routinely exposed to less serious crimes were more likely to impose extreme sentences when confronted with serious crimes when compared to judges who routinely handled

[15] Robel (1990) drew her qualitative responses from several surveys produced by Federal Courts Study Committee in the late 1980s.

serious crimes. In addition to factors that were endogenous to court work flow, judicial practice has also been found to respond to outside stimuli. In a study of Louisiana judges over 15 years, it was found that judges who attended Louisiana State University (hereinafter "LSU") as undergraduates were more likely to impose higher sentences to juveniles in weeks after the LSU football team suffered upset losses, in contrast to the rulings of judges who did not attend LSU as undergraduates whose rulings were not impacted by those upsets. The conclusion of the researchers was that major events outside of court systems and judicial work flows could systematically impact judicial decision making (Eren & Mocan, 2016). These examples serve to further illustrate the fact that judicial systems are not neutral arbiters of law and fact, but too systems that are sensitive to carrying capacity in their own kinds of monetary, human, bureaucratic, temporal, and physical capital.

More limited are studies that suggest the interrelationship between these judicial realities and child welfare practice. Qualitative research has indicated the importance of the court system in the work life of a child welfare worker (Lens, et al., 2016; Carnochan, et al., 2006; Smith & Donovan, 2003). Some quantitative research, however, has suggested that the judicial system places constraints on child welfare practice (Courtney & Hook, 2012; Bass, et al., 2008; Peters, et al., 2002).

2.2.3 Synthesis—A Child Welfare System

Based on this, some predictions can be made.

It is common-sense conventional wisdom amongst practitioners, policymakers, and academics alike that the child welfare system is resource constrained. To a degree, that insight is borne out within the literature. There are limits, however, to what existing literature can tell us about capacity constraints within the child welfare system. First, and perhaps most importantly, there is scant empirical literature on whether the child welfare system is a system in the technical sense described above (Wulczyn & Halloran, 2017). This is a critical empirical question, as described in Chapter 1, because purposive systems in certain classes display characteristic behaviors. In addition to systems treatment, studies of iterative change over time rarely occur at practice-relevant time intervals (Abbott, 2016; Tuma & Hannan, 1986). Based on the theory and literature, we can predict that, in a technical sense, out-of-home care and child welfare courts are part of a larger child welfare system, and that there is empirical significance attached to that classification.

Moreover, we can predict that resource constraints acting through feedback loops within the system will act to shape child welfare practice (Lipsky, 2010). Importantly, these constraints and this feedback will operate not only within the out-of-home care subsystem and the dependency court subsystem, but between those systems—linking capacity and feedback within the out-of-home care subsystem to practice within the dependency court subsystem (and vice versa).

Reframing the question posed at the beginning of this section: If we might expect to see interrelated dynamic processes driven by negative feedback and partial adjustment loops in the child welfare system, how do we detect those processes?

2.3 The Present Study

Building on the preliminary research which indicates some evidence of dynamic coupling (Wulczyn & Halloran 2018; Wulczyn & Halloran, 2017), the present study seeks to situate systems thinking within the context of everyday child welfare practice (Lipsky, 2010) and identify patterns within time series data which may impact practice on a granular level. Because this is an emerging area of research, this study takes a two-pronged approach. First, work to bound the study within the real practice environment of street-level workers involved in the child welfare system. Second, to focus on systematic coupling over time of entries and exits in the out-of-home care subsystem and case openings and closings in the court subsystem, seeking patterning within and between those subsystems.

2.3.1 Systems in a Practice Setting

As discussed in Chapter 1, child welfare decisions are embedded in dynamic practice environments (Abbott, 2016; Lipsky, 2010). In moving coupled dynamic time series analysis from theoretical proposition to practical application, the first step must be bounding subsequent analysis in practice reality. This is especially true where we see some empirical evidence of dynamic behavior shaping the flow of child welfare populations (Wulczyn & Halloran, 2017). To that end, the first analytic step in the present study is a limited qualitative inquiry intended to give child welfare and court practitioners who work in these systems the ability to inform my thinking about how populations are conceptualized and acted upon in practice, the degree to which practitioners sense rates of change in populations, and the ways in which information about populations is communicated. The goal of the qualitative study was to assist in conceptualizing the quantitative modelling presented in later chapters.

2.3.2 Hypotheses

This section describes two hypotheses which arise out of the theory and literature discussed above. These hypotheses drive the assembly of the data and method in Chapters 4 and 5, and are addressed by the analysis in Chapters 6 and 7.

Because a persistent feature of social service delivery is the number of clients on a caseload, system-wide caseload dynamics can be situated as the object of inquiry. The patterns between actions over time (Abbott, 2016) in the child welfare system—entries into and exits out of out-of-home care, and openings and closings of dependency court cases—will manifest themselves differently if decision makers are reviewing cases atomistically or viewing them in the population context (Wulczyn, 1986; Emerson, 1983). Thus,

1) Structured population behavior in the child welfare system will be apparent as coupled entry and exit dynamics within population-level time series.

If such non-random coupled behavior exists, then it is necessary to explore the bounds of the system. Decision-making processes and case flow within dependency courts and out-of-home care are intertwined (Smith & Donovan, 2003), though courts and out-of-home care systems are infrequently analyzed together (Courtney & Hook, 2012; Peters, 2012). If the intertwining of dependency courts and out-of-home care subsystems creates system structures, then

2) Out-of-home care subsystems and dependency court subsystems interact at the population level and constraints on one subsystem will manifest themselves in coupled population-level time series for the other subsystem.

Chapter 3:
Populations and Dynamics in the Practice Context

This chapter is based on the reflections of key informants with experience in the out-of-home care and dependency court settings. This chapter seeks to illuminate qualitative information that will help place the quantitative methods described in Chapters 4 and beyond into a frame, both in terms of time and space, which is meaningful in the practice context. The central purpose of this limited qualitative study was to inform my approach to subsequent quantitative analysis by clarifying certain decision points related to temporal and geographic scope.

A secondary purpose is to provide general empirical support for the theoretical underpinnings of this study by exploring participant narratives related to the child welfare system's sensitivity to population-level indicators and the feedback and adjustment mechanisms. One may ask: if practitioners are not aware of populations and the ways in which they change, does that invalidate the heuristic? In short, no. System theory does not require conscious or intentional conduct on the part of agents within the system. But if the narratives of the practitioners are consistent with population dynamics theories then that provides strong evidence of the real-world salience of populations in child welfare practice.

This chapter proceeds in five sections. First, as an initial matter, I provide an extended discussion of practice in the Washington State child welfare system. Then I turn to the qualitative study. The second section is a brief rationale for an exploratory qualitative study used to frame the quantitative method used in this dissertation. The third section describes methods of qualitative inquiry, with the fourth section describing the results of the qualitative inquiry. The chapter concludes with a discussion of the qualitative findings.

3.1 Rationale for Qualitative Support

Though the primary focus of this project will be quantitative understanding of the population dynamics of child welfare court and out-of-home care systems, there are limits to which these kinds of statistical modeling techniques can represent reality—for example naive models may not fit practice realities, the modeled horizon of practice (temporally and geographically) may differ from practice, patterns which appear to be clear in the data may not be as significant in reality, biases of the researcher may lead to inaccurate assumptions. In order to apply the heuristic described in Chapter 2 to quantitative data, bounds need to be placed around those analyses. Specifically, choices need to be made about temporal (is the feedback response rendered in days, weeks, months?), geographic (should the analysis be bounded by county or state?), and systemic (does the heuristic apply to the child welfare system, the court system, or both?) factors. The primary purpose of this limited quantitative inquiry is to provide data which grounds, a priori, in the experience of child welfare practice those bounding decisions made in the quantitative analysis, described in Chapters 4 through 7. Population-level factors can influence practice in obvious and nonobvious ways, as well as in ways that are detectable and undetectable by practitioners, situating the quantitative exploration of population phenomena within the real-world practice environments of individuals who are working with and managing that population provides insights which may support assumptions within the heuristic and critical details which will shape the temporal and geographic scope of the quantitative analysis.

While exploring the temporal, geographic, and systemic bounds of child welfare practice, the qualitative inquiry provided an opportunity to explore whether the narratives of child welfare practitioners are consistent with population thinking and population dynamics theory. The theory presented in Chapters 1 and 2 assumes certain behavior within the child welfare system. In its strongest form, this behavior includes practice knowledge about populations within the system, along with a flow of communication about population size and feedback loops which govern actions related to population size. If the narratives of professionals contain evidence of the salience of populations on thinking and practice, that presents a strong case for the application of the theory. Should certain conditions exist, like the salience of populations and routine inter-agent practitioner feedback about populations, that strengthens the justification for the application of the heuristic, and may suggest leverage points for the application of the heuristic in a practice context.

While prior research has picked around the edges of these questions (e.g., Smith and Donovan, 2003), this limited qualitative investigation attempts to provide more focused support for the heuristic. A qualitative study is appropriate for investigating these questions because the flexible, open-ended nature of the inquiry illuminates complexity within the ground-up context of the practice environment (Smith & Donovan, 2003; Patton, 2001). Qualitative studies are also appropriate for assisting in the interpretation and contextualization of quantitative models and variables (Murphy & Goodson, 2007).

3.2 Method of Qualitative Inquiry

The method of qualitative investigation in this study is focused on the identification of testable hypothesized features—relationships that suggest the existence of dynamics which shape the way that child welfare populations fluctuate across time. Unlike interpretive studies, therefore, the method of this study employs a pragmatic and positivist posture by using deductive forms to identify hypothesized features of dynamics in child welfare populations (Lin, 1998; Patton, 2001).

The following section is broken into three parts: participant recruitment, interviews, and analysis.

3.2.1 Participant recruitment

Participants for qualitative interviews were recruited using nonprobabilistic, purposive snowball sampling within two counties in Washington State. This sampling method was selected for several reasons. Purposive sampling was used to ensure inclusion of multiple viewpoints and to provide breadth of perspectives. Snowball sampling allowed access to informants identified as knowledgeable within the context of the system by other professionals working within that system.

On July 15, 2015, I made initial contact with the primary node in this study when I replied to a communication on a child welfare listserv. I asked for assistance in locating knowledgeable professionals in two Washington State counties who might be interested in assisting me with a research project. The sample criterion, shared with the primary node, was a diverse set of roles and perspectives of individuals working directly in the child welfare and dependency court systems. This primary node was able to introduce me, by email, to four key secondary nodes within the focus counties.

Following those introductions, I corresponded with the secondary nodes introducing myself, explaining my research, and asking for assistance in

> contacting key participants in the child welfare system in Washington to try to understand how caseloads, resources, and the interrelationship between courts and the administrative agency impacts child welfare practice in the courts and in agencies. I am in the process of recruiting attorneys (parent, state, and child's),

> judges, case workers, and case supervisors to participate in an interview on those topics. I would like to speak to one or two professionals in each of those categories in [your c]ounty.

(Secondary Node Personal Correspondence, August 21, 2015). Three of the four secondary nodes followed up on this introduction and initial correspondence. By email and by phone I asked for introductions to key professionals in dependency court. From these three secondary nodes, I was introduced to twenty-two professionals working in child welfare and dependency court systems within those two counties. Initial correspondence with secondary nodes took place between August 20, 2015 and September 17, 2015. Following introductions by secondary nodes, I recruited the professionals by email between September 18, 2015 and January 4, 2016. Seventeen agreed to be interviewed, but four potential participants were eliminated because of a duplication of roles. The participants for the scheduled interviews were purposively selected for a diversity of viewpoints and roles within the child welfare and dependency court systems. The final sample included two judicial officers, three representatives of the Washington State Department of Social and Health Services' Children's Administration (hereafter "Children's Administration"), three parent attorneys, two Washington State Assistant Attorneys General, three child representatives (including two child attorneys and one Court Appointed Special Advocate). Six participants worked full-time on child welfare matters, with four others dedicating more than fifty percent of their work time to child welfare. The remaining three people in the sample spent less than fifty percent of their time working in dependency court. The three Children's Administration participants are currently administrators or area administrators. However, each has experience as a front-line worker and a front-line supervisor, and they were asked to draw from that experience when answering some questions. Participants ranged in experience in child welfare at the time of the interview from just over a year to almost three decades work in the field, with most participants having more than ten years of experience. In order to protect the anonymity of participants, names, titles, roles, and geographic locations are not used within this chapter.

3.2.2 Interviews

There were thirteen interviews conducted. At the beginning of the interview, each participant was asked for, and gave, verbal consent to the interview and verbal consent to record the interview. Interviews were conducted between September 11, 2015 and January 27, 2016. The interviews were over-the-phone and semi-structured, based on an interview guide, but open to follow-up questions for clarity and detail.[1] The interviews were recorded on a digital recorder and professionally transcribed. Interviews lasted between 25 and 70 minutes, for a total interview time of eight hours and fifty-nine minutes. This resulted in a total of 284 transcribed pages.

3.2.3 Analysis

The purpose of this analysis is to connect the experiences and perceptions of front-line dependency court personnel to population-level influences in order to identify the general existence of both "signal" generated by hypothesized population dynamics and the mechanisms which undergird those dynamics (see Smith & Donovan, 2003). Categories for analysis were defined by the semi-structured interview guide. Interviews were hand coded based on four primary categories: (1) sense of population size; (2) sense of rate of change; (3) information flow amongst workers in the system; and (4) differences in practice based on population factors.

Following each interview, I listened to the recording and made general notes on the dominant themes in the conversation. I listened to each recorded interview again while following along in the transcript to check for transcription errors. After that initial transcription check, I

[1] The complete interview guide can be found in Appendix B.

coded each transcribed interview by hand in accordance to the above-delineated categories. Primary categories were then assessed for frequency of general patterns and organized into representative responses.

3.3 Qualitative Justification for the Application of Heuristic

This section begins by discussing ways in which information about child population flows among the street-level workers and continues by reporting the sense that street-level workers have about the overall size and rate of change of the child population in out-of-home care and in dependency court. Next, I report participants perception of impact on practice of the impact of changing populations of children in out-of-home care and cases in dependency court. This section concludes with participant insights on how time and space relate to their perceptions of population size and change. In the following sections, material in standard quotes and block quotes is drawn verbatim from participant interviews.

3.3.1 Information Flow

An ongoing theme concerning the way information about populations flows among and between workers, attorneys, and judges is illustrated by the following quote from a parent attorney: “The folks who practice dependency are a pretty small group.” Consequently, though meetings and other formal moments of communication occur frequently, all participants emphasized the importance of collegiality, tight networks, and frequent opportunities for informal discussion as the main forums for understanding the state of the dependency court and out-of-home care population. To this point, one Assistant Attorney General said, “I think a lot of us know each other personally. When you work with the same people year after year, at least for me, I get to know them personally.”

In one county, the court call is organized so that workers and lawyers spend extended periods of time together. Several participants noted that it is as an opportunity to build relationships, to get on the same page about cases, and to share general information about dependency court. One child welfare administrator described that routine weekly interaction as follows:

> [S]o even if a certain case isn't on the docket, I'll grab somebody else's lawyer and just sort of do a check-in every—almost every week, like, "hey Jim, Susie's not doing her UA's, what's up?" So I mean, I don't wait and spring it on people, I try to keep everybody up to date as we go along so there's no surprises, and I think that that ultimately makes it go quicker because then you don't have lawyers up there standing up there going we didn't have any idea they weren't doing it. Yeah, you do, I told you every week they were or weren't doing it.

Though matters were handled differently in court in the other county, some participants noted that court scheduling created a generative moment where child welfare workers could frequently interact with each other and with attorneys in an informal environment. Another child welfare administrator similarly describes routine court times as an opportunity to informally network on specific cases and move those cases along—especially with cases that are not on the court calendar for that particular day. That participant said:

> I'm just old and I've been around a long time and I'm a talker and I know everybody and I'm a schmoozer, so I get a lot of work done just standing around talking to people like 'hey, you know your client is screwing up, what are we going to do here? Here is what I'm willing to do.' And I feel like that gets a lot probably more done than the formal piece.

Attorney participants indicated that on days they are in court, that they frequently spend all day in court. One child welfare administrator said that on court days, "Basically most of the day we're over there interacting." This results in the courthouse being a petri dish for systemic collaboration. One judicial officer said, "If you were to sit in [] there's a lot of moving parts going on. People are talking. Negotiating." Another judicial officer credited "[c]onstant judicial prodding" in and out of court with keeping social workers and attorneys "on board." One child welfare administrator noted that this routine informal court house interaction, and the relationships and trust that those interactions build among the small dependency-court working group specifically helps to facilitate information flow and ease contentiousness:

> I think informally, it's not as much a conversation as just an understanding. But I think it's also a lot about how you present it. If you're basically standing in front of the commissioner and the lawyer's saying, 'Why haven't you helped my client do A, B, C or whatever?' and you're 'I'm really busy, I have twenty-seven kids on my caseload' that's whiny. Whereas, if you say 'Because of workload pressure, I have not gotten to that, but I will tell you by Friday at noon that that referral will be sent in' that defuses people.

This illustrates not only the frequency of the informal interactions, but also clarifies the incentives for building these relationships. An Assistant Attorney General similarly relayed the importance of informal communications among the attorneys and judicial officers, and noted the frequency of informal communication saying:

> Mainly between the [Office of the Attorney General] and the commissioner. And the [Office of the Attorney General] and opposing counsel—parents' counsel and children's counsel—and the commissioner. But it's all off the record. Yeah, it's all off docket. Off the record. But there are many times when the docket is over for the week and you might have two or three attorneys sitting there trying to catch up with their orders or whatever and the commissioner will step down off the bench and sometimes [the commissioner] will say, 'What's the data on such and so.' Or 'I notice that we're not getting kids into foster homes, when is that going to change?' Or whatever.

All participants indicated some regular, formal opportunities to discuss child welfare practice. An Assistant Attorney General describes these different formal meetings as going beyond caseloads to discuss the operations of the dependency court,

> We've had for years and years annual meetings where we try to

> talk about things on a bigger scale and what can be improved. And then we have meetings on a regular basis—it's varied from monthly to quarterly to a couple times a year sort of depending on the judge and what's going on. To address things. And that includes things from the annual as well as the monthly or quarterly meetings. The judge and CASA, [Children's Administration] supervisors, and OPD—the [OPD] attorneys—children's attorneys, and the Assistant Attorney Generals [sic.].
>
> This commissioner started a few years ago a subcommittee of people that meets prior to the quarterly meetings—I've been attending those as well—where we try to each represent our own agency—so that's there's only one or two [Assistant Attorneys General], one or two children's attorneys one or two OPD. We meet and try to discuss areas of concern prior to that coming to the entire group because some of those bigger meetings can get unwieldy with so many people there.

Changing caseloads are important topics in regular monthly meetings among dependency court and child welfare staff. One child representative said:

> That comes up as a topic of conversation at [our monthly meeting], particularly if things are going up or down. There's a pretty keen awareness of how many dependency filings there are each year. Not so much how many dismissals there are. But we definitely know the number of cases.

In addition to illustrating the importance of meetings in creating knowledge about populations, the above quote also serves as an example of the ways in which overall population size and population change tend to merge in conversations.

One parent attorney reported that, "communication is something that typically in [this county] we have put a real, that's been a real priority for us. And, you know, something we really encourage between us and the Department and [the court] and the [Attorney General]'s Office." In one county, formal meetings contained explicit feedback about caseload. One child representative said:

> I think in our system I think everybody's pretty aware of what everybody is doing because we do have the regular meetings and

> we have numbers that are presented at the meetings. … [W]e track that anyway so every month we're finding out how many new filings there were, we know how many hearings there were ….

Monthly meetings of dependency court personnel took a more macro, systems view of the child welfare caseload, and attempted to address more systemic questions and problems as opposed to individual case-level concerns. According to one parent attorney:

> [I]t was really a time for you know, like twelve of us to get together and have a good conversation about things that needed to change, things that weren't going well, and we really worked as a team. And it was at least one person from each discipline: so one defense attorney from [the public defender's office]; one defense attorney from OPD, because we come at things from kind of a different perspective, and then one [Assistant Attorney General], one social worker, and the judge.

Described by another participant, a child representative, these meetings, sometimes with a formal agenda and sometimes not, were gatherings where

> we all just kind of meet and go through, like, you know, different issues, or, you know, things going on in dependency cases in [our county]. Concerns the Commissioner has seen or things that have been brought up. And there are representatives for each, like, group.

Another participant, a judicial officer, described these meetings as an opportunity "to bring up issues of mutual concern." An Assistant Attorney General amplified that, "[The commissioner] wants to talk about the issues. To know what's going on."

Information at these meetings, however, did not necessarily flow freely between those involved in dependency court. A parent attorney indicated that the quality of these regular meetings depended greatly on the participants—with some meetings turning more into a directive "telling us how it's going to be" rather than "a democratic system where we're all working as a team …."

Additionally, subgroups of practitioners have initiated regular monthly meetings to, as one parent representative said, “just sort of share ideas, and, so, at those meetings we kind of take the pulse of dependency and see what’s going on.” In one county, informal weekly Wednesday lunches also promote the exchange of information between participants, where another parent representative said, “whoever can show up shows up and that’s been a real kind of fun bonding thing.” In the same county, there is a monthly organized happy hour designed to make connections outside of the courtroom. The same parent representative who spoke about the Wednesday lunches credits these informal opportunities as being

> really good all the way around in terms of resolving issues on cases and having somebody that you maybe have a little bit more of a personal relationship with to go to and say, ‘I am going to kill this social worker if something doesn’t happen. Can you help me?’ … So, I think generally communication is pretty good.

In the dependency court setting in these two counties, informal opportunities to interact with colleagues were emphasized by the majority of participants as being as or more important than formal meetings to facilitate information flow.

A barrier to information flow between the attorneys and the Children’s Administration caseworkers is the frequent turnover amongst the caseworker ranks. Several attorney participants lamented the fact that they don’t have continuing relationships with caseworkers because of the turnover. An Assistant Attorney General noted frustration with social worker turnover, “[T]hey’re here and then they’re gone so quickly and then we have another one.” That participant continued by saying that the result of this is that the Attorney General’s Office is “constantly training new social workers about what they need to do in the legal arena. … And we end up fixing a lot of mistakes. Or going to court without all of the information that we need.”

One parent attorney noted, “I have cases—a number of cases—that have had six or seven social workers in a year.” Another parent attorney stated:

> It used to be just a different culture, you knew everybody, and everybody had been there for a while. Every once in a while, there’d be a new person. It was like typical turnover with any other business. But it’s not like that now. I mean now you go into court and you pretty much don’t know any of the social workers because they’re all brand new. That makes it pretty difficult. I think when the social workers are new, not only do they not know what to do, but they don’t trust you so they always think you’re trying to get them to do something that maybe they shouldn’t be doing. So, it really kind of brings the process to a halt because everything you’re proposing they’re just not sure about and they’re really skeptical so then they’re going to their supervisor, you know, maybe three days later when they think of it to have a conversation about whether or not what you’re proposing is appropriate and then they take action. Everything is just going much slower and there are lots of excuses.

The above quote serves to emphasize the importance of repeated play in the small community of child welfare professionals. Unclear communications and unfamiliar participants create barriers to the process, that robust communication opportunities can overcome.

3.3.2 Sense of Population Size

All participants reported some sense of the overall population size of children in out-of-home care in their counties. One child welfare administrator said, “So all the way from our administration to our line workers, everyone is a very aware of what caseloads look like and children coming into care.” The child welfare and dependency court personnel interviewed for this study discussed the population of children involved in the child welfare system primarily through caseload and workload—both at the individual level and at the county and state system level. Caseloads were directly addressed in both formal and informal discussions amongst child welfare and dependency court personnel. Participants indicated that statistics on new case openings, how many cases went to reunification, and how many cases went to adoption are regular agenda items in meetings amongst dependency court personnel. In addition to more systematic caseload discussions, participants indicated frequent peer-to-peer interactions on business and stress level and observational indicators about how a courtroom looks or feels.

Participants reported that they regularly receive some official or semi-official information about the size of the out-of-home care population or the number of cases on the dependency court docket. This official information took on two forms: (1) regular interagency meetings (monthly or quarterly) of child welfare personnel—as discussed in Part 3.4.1 above—where caseloads were discussed; and (2) administrative or judicial statistics about the population. Though the purpose of this official or semi-official information was not always exclusively focused on caseloads, most participants indicated some agency- or court-level emphasis on the size of populations. There were times when populations became focal points. One parent attorney indicated that caseload conversations come up when the court, the administrative agency, or one of the attorney departments wants to make a change, but the front-line attorneys, as that parent attorney said, cannot "accommodate that because of how our day is set up."

Another official indicator of population size is in the caseload carried by street-level workers. For example, one child representative noted that

> I notice though that a lot of times the parent[] attorneys will be over [the caseload they are allowed in] their contract. Sometimes they're not, like last week it seemed like everyone was kind of under it, but sometimes they'll send out emails and almost everyone will be over, like, what their contract is for.

Thus among at least one group of workers there is a very time-sensitive semi-official mechanism for indicating some threshold population size.

In addition to formal methods of learning about population size, participants use personal and community indicators to contrast high and low volume moments. Most participants indicated the interrelationship between overall caseload volume and workload. One Assistant Attorney General discussed the connection of workload and caseload, saying “I was fairly stunned by the expectations and the lack of time that is allowed.” Commenting on smaller caseloads, one judicial officer noted, “It’s just less, to be blunt: less stress, less prep work.” That same participant continued by saying,

> I have no built-in prep time before anything. So you’re prepping before court, before the docket starts you’re prepping, you’re working during your lunch. In general and you’re hoping that your—and I hate to say it this way, but it’s true—you’re hoping your trial settles so you have prep time to read for the docket.

Sometimes, however, workload and caseload are not related. Composition of individual caseloads can confuse the connection between population and workload. In some cases this has to do with the nature of the cases on the caseload—some participants indicate that there are times where cases seem like they take a lot of work. One parent attorney said,

> [T]he caseload idea is just ridiculous to me because you can have eighty cases that are all incredibly calm and you can be, you know, working a three-day work week or you can have eighty cases and half of them are out of control and you’re working nights and weekends. So to put a number on the cases rather than weight the cases based on the amount of time each case is taking in a week is just—I think that is like the most ridiculous idea that I have ever heard ….

An Assistant Attorney General amplified that, saying, “I mean there’s some cases that really require very little work compared to other ones that just chew up an incredible amount of time where there’s just a lot of conflict and needing to address variety of situations going on in the case.” Additionally, external factors can also impact the perceived workload of a given worker’s caseload. Another parent attorney also noted the workload impact of caseworker turnover on attorneys, saying, “[in] fifteen to twenty percent of the cases where maybe I don’t have a good social worker [], I better just know at every moment what has happened in that case at the moment.” Another example of this is when organizational factors increase the amount of work required per case. The same parent attorney said:

> I think there are more cases being filed, but I also think that the judges are setting a lot of 30-day status conferences to check on how things are going, which can sometimes be a good thing, because they’re, you know, any time you’re in front of the judge more often, you’re probably getting better results. Or at least moving the case forward in one direction of the other. But I think the status conferences are adding a lot of extra hearings to the docket ….

Thus, judicial preferences in hearing calendaring can significantly increase the individual workload of participants just based on the frequency of court appearances without a relative increase in overall caseload numbers.

Some participants also indicated that the number of people in the courtroom or courthouse provided some insight on the population of children in out-of-home care. One judicial officer said that when the volume is high that “the courtroom is just a lot more crowded.” Participants indicated ocular feedback about caseload in the week-to-week physical number of people in the court or on the docket. A child representative also indicated, “It’s just the number of people, it’s always crowded.”

Another way that caseload is assessed is by the severity of the case allegations. One judicial officer stated:

> And we talk about that pretty regularly, certainly the judicial officers, are you seeing any what I call fluff? Are you seeing anything that’s, like, that’s a close call? And it’s like, no. Because especially when the numbers are up … then we’re really looking at them. I would fill in occasionally for a week or two when someone was on vacation and really be scrutinizing these petitions to say,

> well, you know, is this really necessary? And it's like, they are. I mean they're pretty serious.

Thus, for this participant there is some caseload composition related to severity that indicates overall case volume.

A final way that participants received feedback from their peers about population volume was through interpersonal wellbeing indicators. For example, one parent attorney associated stress with work volume

> I would say that this is a time where most of the attorneys are just more stressed than they've ever been. Working harder than they've ever worked. It's probably the busiest I've ever seen it in the however long I've been here.

An Assistant Attorney General shared a story about managing information in their practice:

> I get a ton of email. And [case workers] will communicate quickly and often about everything—even about things that are not relevant. Occasionally, I will get a phone call. They don't use the phone as much as email. The email is just constant. I was speaking to my district supervisor one day, and he wanted to meet in my office and he was sitting in the office, and my emails were coming in so fast that it was pinging constantly. He said, 'Would you turn that off?' Because it was just constant. And he said, 'How many emails do you get a day?' And I said, 'About 175.' And he was shocked. … I can't respond to all of those. The best that I can do is file them. It's really stressful sometimes. What if one of these is important?

A parent attorney detailed how workload and stress impacted practice priorities:

> One of the reasons I think it's so stressful for everyone is because the dockets are so full and there's so much going on, we've kind of switched from first a priority from having a meaningful hearing to making sure the docket is done at lunchtime because we can't handle not eating before the afternoon docket, you know?

One judicial officer stated, "I do believe that we have less than a hundred on the docket—I'm a really happy person, because we typically have one hundred or more on the docket." Participants look to their personal stress levels, as well as those of their peers, to indicate the overall size of the population.

3.3.3 Sense of Rate of Change

Related to overall population size, participants were also asked to speak about if and how they knew that court and out-of-home care populations were growing or shrinking. In many cases, conversations about rate of change and the overall sense of the population size bled together. Two attorney-participants indicated that they were not experienced enough to have a sense for how populations change. Nevertheless, all participants noted that, similar to overall population size, official and semi-official indicators were used to identify changing populations. Among those indicators were regular meetings where month-to-month or year-to-year changes were discussed along with contractual case limits for dependency court attorneys.

Some participants situate these population changes within a historical context. One judicial officer said:

> You know, five, six years ago, our normal would be about twenty new cases a month. And now the new normal is fifty or sixty and all of those are typically going to last two or three years because, you know, it takes a long time to get out.

Though some participants phrased this change on a year-to-year time scale, others placed it in months or weeks. One child representative noted that times of very rapid change in population would receive attention in routine monthly meetings. That participant said,

> In 2010, we went from an average of 35 dependency petitions a month to over, we had like, 120 in one month. So that was a huge swing. Now they're an average of about 55 to 65 petitions a month. And I think if there was—like I would probably bring it up if it went into the upper 70s. […] If it was in the 40s one month it wouldn't come up. If it became consistent we might bring it up. Definitely if it was below 40, I think we would have a conversation—what we usually find out is that they had some

> policy change at [the Children's Administration] where there's a training.

This indicates a fairly prompt feedback mechanism to assess whether populations are changing.

Similar to overall population size, the use of contract attorneys with contract limits also provides a feedback mechanism on a relatively fine-grained time scale. Several participants indicated that regression of caseload back to under contractual limits is something that happens in a matter of weeks. One child representative said, "[s]ometimes it could be a week … it could be a week or it could be, like, several weeks where they're over before they close out [and return to contractual limits]."

Several participants reported that court dockets served as a semi-official indicator of changing population size. I refer to the dockets as a semi-official indicator because what participants were observing in dockets were specific types of hearings and scheduling complications. One way that participants said that they knew of particularly increasingly busy periods was the length of certain portions of the court call. For example, one parent attorney indicated:

> Generally it's just a sense. We can tell by, 'you know, gosh, there have been three shelter cares this week instead of remember a year ago when we were doing six a day?' And then, you know, then that translates into the fact-finding docket and how many new cases any of us are getting at any given time.

The translation of shelter care, or initial out-of-home care placement, hearings into down-the-pipe docket complications was addressed by several participants. One judicial officer noted that:

> I think we are way more attuned to it when there are more incoming because of the way it's structured and everything's set at the same time. So we've got the fact finding hearing Tuesday afternoon and when that docket's got seventy cases on it it's kind of hard. It's more manageable if it's thirty, which sounds kind of silly, but, you know, just being able to figure out how to get

> through the cases and you see that bubble go through the system and you see that outlier.

The other judicial officer said, “[I]f there is a huge increase one month, how we’re dealing with that and how we’ll sort of move the dockets around to accommodate if there’s a big explosion one month. You never know what causes that stuff.” The idea that scheduling attention needs to be paid to case openings to mitigate the impact of any downstream “bubble” is one way in which participants indicated sensitivity to changing populations.

In addition to official and semi-official indicators, there are also informal indicators of change in population size. One Assistant Attorney General said, “We don’t have much downtime … I haven’t had much downtime here since I started ….” A parent attorney chalked the sense of population size as horse sense, stating, “We always know when […] there were huge surges in the number of filings, you know, for various and sundry reasons.” Another, a child welfare administrator, felt change in terms of light case filings, noting that “[e]verybody would know when there were certain lulls. And holidays and things like that. Any more, it feels like there hasn’t been a lull in a couple of years. It’s just slammin’ all the time.” As again illustrated in the above quote, participants frequently mingled discussion of change in population with perceptions of overall population size. While a minority of participants reported the “feel” of changing populations, there may be a relationship of this kind of perception to reporting a “feel” of overall population size.

3.3.4 Differences in Practice Based on Population Factors

All participants were asked about how their practice, and the practice of others in the system, changes based on the volume of children in out-of-home care or the rate of change in the out-of-home care population. The reaction of most participants was that, in general, they did not perceive practice to be particularly responsive to population. Several participants indicated there were specific changes in policy related to populations that provoked practice changes (attorney case limits and case timelines, for example). All participants, however, noted changes in their own practice or in the practice of the system as caseload and workload changed.

When the caseload volume is high, some participants indicated an increased deference to the Children's Administration. One child representative indicated the tendency of the court to "rubber stamp" what the Children's Administration is doing, continuing to say:

> [The Children's Administration] is given way too much leeway with being able to do stuff not in compliance with the statute and the court, because they are so busy, is just kind of 'okay, that's fine, we'll go with [the Children's Administration's] suggestion' without really looking into it or being critical of what [the Children's Administration] has chosen to do.

A child welfare administrator remarked, "[Parent attorneys] have an incredible caseload and they're not going to put the effort into somebody that's being a jerk and never keeps up with them and they don't know what's going on or makes them look dumb when they're standing up going, 'I don't know, I haven't found my client.'" Both deference to the Children's Administration and less willingness to work with clients, particularly difficult clients, were perceived as different responses to manage judicial and attorney workload in busy times. Correspondingly, a different participant noted that smaller caseloads give participants an opportunity to pay more attention to individual cases. A judicial officer said,

> [A smaller caseload] means that potentially we can give more time in court to actually have a—well, I won't say a full hearing—but to give more time to people to express themselves. If you have [a bigger caseload] then you get about three to five minutes. Which is not right. But that's the way it is.

An Assistant Attorney general discussed the inverse, saying

> What I see at the [Children's Administration] is that they are beyond capacity. Their caseload should be around twelve to fifteen cases, and some of them now have twenty-eight cases. So they really feel, from me talking to them personally—the ones who I have talked to personally—they're doing their job, but they feel very torn. Like they never really have the time to do a good job, they feel like they're constantly being torn between all of these things that are coming up and happening, and there are lots of fluid facts in these cases because things are changing constantly. So lots of them are really stressed. And there is a lot of turnover.

Similarly, a parent attorney discussed placement type as one indicator of work and stress related to cases,

> [I]f they're in a relative placement, I breathe a little sigh of relief—and, you know, there are some shitty relative placements and relatives who hate the parents and all of the rest of that and that's difficult—but to me, those cases are less stressful to some degree than a kid who's in foster care, especially if it's a young child where there's a high likelihood that the foster parents are going to be pushing for an adoption.

Perceived intentional practice changes, then, were couched in terms of more work in the same time and less attention available for the work.

Put simply by a child welfare administrator, within the system overwork is not an acceptable excuse for lack of action and the attitude is projected as, "That's your problem. Take it up with your agency. You still need to serve the client and do your job." Another child welfare administrator reinforced that concept by saying,

> I know that recently [the judicial officer has] been vexed with social workers telling [them] they weren't able to get a court report done or they weren't able to do court-ordered service referrals because of workload. And [the judicial officer] expressed very strongly that [they don't] consider that to be an excuse.

These comments from the agency show the pressures that are placed on workers to accomplish tasks in times of high caseload, and the ways that they are checked to make sure that they are accomplishing more work in the same time.

Though some participants indicated periodic difficulty in setting court hearings based on the overall volume of cases, other participants suggested that courts just “make room” for short-notice hearings. One parent attorney said, “I think they just squeeze it in, to be honest. And I think they give that case a little less time so they can fit this case into the docket.” On the other hand, one judicial officer noted that when there were lots of children in out-of-home care that there was less of a willingness to file dependency cases. That participant said,

> I think the volume is such that they don’t want to file any more than they have to. … You know, if we had an unlimited amount of social worker and CPS worker staff? You know, maybe that would be different.

This tension between the perceived willingness to squeeze in work and perceived unwillingness to add to the population is suggestive of some practice-level response to changing populations.

Some policy tools that have been used to control or limit caseloads have sometimes ended up in changes in practice. Several participants noted that one example of this is the OPD limit of eighty total cases that parent representatives can carry. The OPD regularly checks the caseload numbers of parent representatives before assigning new cases. In practice, though, respondents indicated that the movement of cases onto and off of caseloads creates frequent situations where private parent representatives are over their caseload limits. Similarly, other participants indicated the OPD caseload cap has influenced state-mandated caseload requirements for children’s representatives—also capped at 80.

Another example of policies which impact workload and practice are training and retraining requirements. One Assistant Attorney General said,

> I feel like it’s always extremely high pressure to do too much. … When there’s a new policy that’s brought out and they have to do things differently and go through training and that takes a chunk of time as well. When they have to do more visits and supervise them that takes a big—that raises the level of stress.

This again frames feedback mechanisms and changes in practice in terms of pressure and stress. Another example of corrective policies amplifying the perception of strain is time limitations placed on adoption finalization following termination of parental rights. One parent attorney said,

> Because as they have pushed to terminations more quickly, and then now there's legislation that really pushes them to get adoptions finalized within six months of the termination of parental rights, what we're seeing are a lot of failed adoptions.

Thus, a policy responsive, in part, to caseload and time in care has, in the perception of this respondent, created additional system strain and caused practitioners to respond in kind.

3.3.5 Horizons

Transitioning from broader empirical supports for the heuristic into practical tools for refining quantitative models discussed in Chapters 4 and 5, this section will discuss, in turn, temporal, geographical, systemic frames.

3.3.5.1 Time

Participants indicate that the temporal scope of the work in child welfare is day-to-day or week-to-week. Though there are monthly, quarterly, and yearly indicators of system performance that are discussed amongst participants and which are salient for planning purposes, it is daily and weekly calendaring (and week-focused court calendaring) which drives the perception of availability, business, and capacity. A child welfare administrator noted weekly court calendaring and the importance of weekly contact with lawyers and judicial officers, "In my case, I would say it's over there because every week I figure I have to be there anyway, so even if a certain case isn't on the docket, I'll grab somebody else's lawyer and just sort of do a check-in every—almost every week." One parent attorney noted, "I would say that probably fifty percent of my caseload requires me to touch it once a week …." Another parent attorney placed that number at thirty percent—stating “[they] are pretty demanding, taxing, ‘gotta stay on top of it, have some communication about the case every week’ kind of cases.” An Assistant Attorney General, in referencing the week-to-week or month-to-month nature of dependency cases, said, “I have about ten percent in termination stage. Two percent in guardianship—going to be going to guardianship—or possible relinquishments. I have two open appellate cases that I have briefs due for within the next month. And the rest are dependency.” One judicial officer noted about overall system business, “On some weeks when they’re working hard, they’re running, they’re just trying to stay on top of everything ….” On the whole, the most salient time frame was the week.

Even though cases receive semi-annual reviews in court, the six-month patterning of those hearings does not seem to impact everyday practice. In fact, the extent of the temporal horizon, mentioned by several participants, is a 75-day scheduling limit for fact-finding hearings. One participant, a child welfare administrator, remarked that the 75-day period is “kind of far” in terms of the impact on practice. The salience of this eleven-week period is partly a consequence of judicial and supervisory attention to performance measures which account for scheduling a fact-finding hearing within that limited time period. One parent attorney noted, “Well, it’s pretty clear that it’s been put into people’s evaluations about meeting various deadlines so everyone knows that the 75 days and for terminations getting them filed within 45 days of referral—those are statewide goals and you’re expected to meet them.” Along with these timeline measures, participants noted that annual case filings and out-of-home care placements are discussed at meetings. Even though these performance measures might provoke policy changes, those goals were regarded as more distal and less impactful on day-to-day practice.

3.3.5.2 Geography

Participants indicated that the overwhelmingly vast proportion of their communications about child welfare and dependency court practice took place with professionals based within their main county of practice. Participants indicated having less knowledge of the state system or the regional system than they did of practice in their particular county. One participant's work bridged two different counties, and that participant was active in communicating about child welfare and dependency court matters with people from both counties. Several participants noted that a number of the children on their caseloads were placed across county lines, which required coordination in different geographic locations. Finally, several participants noted that they were (1) employed by organizations that had a statewide presence which expanded their networks[2]; (2) actively engaged with state-wide or region-wide child-welfare or dependency-court improvement efforts; or (3) actively participating in voluntary or professional organizations which crossed county lines. Nevertheless, of the participants participating in regional or statewide communications most either affirmed that most of their knowledge and communication was county-specific or admitted a lack of specific knowledge about caseloads in other places.

One child welfare administrator cautioned against assuming that line workers have too much understanding of what is happening in the system outside of their own work, saying:

> I think staff are more than ever before feeling insulated so they understand what their own workload is like. I don't believe they have a sense of regional perspective and that's new. I'm not sure to what I would attribute that, but I think within the last maybe three to four years there's a lot of new staff, so they don't know people in the other offices. Because they're new and largely the supervisors are new, there's sort of a generalized sense of being overwhelmed and panicked, so whatever their number of cases is, it seems like the most any human being could ever do.

[2] One participant, a child welfare administrator, commented, "I know a lot of people around the state because in my original group a lot of people have disbursed to other offices, and I still stay in touch with those people."

3.3.5.3 Influence of court

The influence of the court, and, in particular, the judicial officer in setting the workflow expectations of the child welfare system was a dominant theme. One child welfare administrator said, frankly, that "court drives our work." Participants indicated that some judicial officers favor collaboration and a "team approach," while other judicial officers are more directive. Several participants indicated the sensitivity of judicial officers to timelines and judicial evaluations based on those timelines. One parent attorney commented that in times of particular sensitivity to timelines that "[i]t was really form over substance …." An Assistant Attorney General noted that as self-imposed deadlines approached that practice became chaotic as workers and attorneys attempted to meet procedural or permanency deadlines, and that there was a significant amount of pressure by the court to ensure deadline compliance.

As discussed previously, the importance of the court was also related to the work that gets done informally during routine weekly court calls, the scheduling of those court dates, regular formal meetings between agencies and courts, and court-based performance measures which are salient to all parties.

3.4 Discussion and Conclusion

This chapter considered, in the main, the following questions: (1) In refining population-level models, how do the experiences and perspectives of street-level practitioners shape the scope of quantitative inquiry in terms of time, space, and extent of interrelationships between the out-of-home care and dependency court practice? (2) In considering population-level effects, do qualitative reports of street-level practitioners reflecting on child welfare and dependency court systems support (a) the theoretical sensitivity to population-level indicators, and (b) the plausibility of feedback and adjustment mechanisms which govern the coupled behavior at the population-level in the underlying theory? This section will analyze begin with the second question and then conclude by analyzing the first.

3.4.1 Qualitative Support for Heuristic

Emerson (1983) suggests a population-level analysis which accounts for the fact that cases within a caseload are processed as a unit. This limited quantitative inquiry suggests that participants experience this as true within out-of-home care and dependency courts, reinforcing the concept that practitioners are sensitive to population-level indicators, and that they receive feedback from those population indicators and adjust their behavior accordingly. The evidence in this chapter provides some support for the plausibility of the process explanations described by the heuristic in Chapter 2 as governing behavior in out-of-home care and dependency court populations.

While participants have a sense of the overall population size, framing that concept in terms of caseload and workload, what was talked about with much more frequency was the opening or closing of individual cases. One of the main indicators of business was how many shelter cares hearings were occurring in a given week, which gave an indication not only of current business but also of increased caseloads at future times. Thus, the events of case openings were, for participants, particularly salient indicators of the work required to manage the overall caseload.

A limitation here is the participant pushback against conflating caseload with workload. Several participants noted situations where workload may be disconnected from overall caseload (see Yamatani, et al., 2009; Juby & Scannapieco, 2007). It may be, then, that workload may be the criterion value around which the system of child welfare dynamically adjusts. This distinction demands further research, but is outside of the scope of this dissertation. Moreover, the model applied here suggests that even if workload is a large part of the latent adjustment parameter that that behavior may be observable in the ways in which entry and exit dynamics pattern. More specifically, Equation 2.5[3] contains a criterion parameter, π, which, while related to entries and exits, may contain additional information about the adjustment to particular organizational goal or objective. Thus, for the purposes of this dissertation, I consider workload considerations as part of the impelling force modelled by π.

Similarly, one of the justifications for the application of the partial adjustment model is that it gives an opportunity to study a system governed by resource constraints when those resources cannot be directly observed on a day-to-day practice timescale (see Abbott, 2016). Participants focused on mainly three types of resources described in Chapter 2: temporal capital, human capital, and bureaucratic capital. Participants spoke about their time constraints and how those intersected with workload and caseload, bringing to mind the importance of thinking about the time required to do a unit of work (see Lopez & Zuniga, 2014). The idea of whether or not work could be "fit in" was prevalent, as was the idea that the workforce was overworked or working at its maximum capacity. This workload limitation also brings to mind the street-level worker's task load, and what is required to get through the work week (Ellett, et al., 2007). For participants, caseload size is related, at least in part, to these bureaucratic burdens. Additionally, participants sketch out a relationship between workload and the human capital in the system. Participants noted that things seem less busy when there is a stable workforce and when that workforce isn't overloaded (see Alwon & Reitz, 2000). Participants also acknowledged the

---

[3] Equation 2.5 is a system of equations where y can be thought of as representing out-of-home care entries, x can be thought of as representing out-of-home care exits, r is a rate of adjustment parameter, and π is a criterion parameter to which the entries and exits adjust:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r'\pi'x(t) - r'y(t)$$
$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = r''\pi''y(t) - r''x(t)$$

existence of funding and placement limitations, bureaucratic capital, that impacted their work. The strain discussed by participants in this study is a common theme in child welfare research (Lens, et al., 2016). Though there are many ways that a street-level worker could manage these constraints (see Lipsky, 2010), one of the mechanisms of control that they most proximately hold is that of managing entries and exits (Wulczyn, 1996). In fact, any one of these forms of capital that exist in the child welfare system could form a potential mechanism for a system of feedback between populations and entries and exits. Moreover, any of these forms of capital could be the latent criterion capacity parameter that the system is adjusting to at any given moment. That is sufficient to justify further exploration of the heuristic.

Participants also reported a vital system of communication between and among street-level workers in the child welfare system. The formal and informal opportunities to share information—including information about workload and caseload, which participants indicated was regularly shared—is a strong indication that the system might be responsive to population-based feedback. Importantly, participants lent support to the idea that those responses might be in a dynamic environment, where future conditions are dependent on responses to past information. This played out several ways in discussions with participants. Most important were the week-to-week check ins that were accompanied by observations about stress and workload. This dynamic information flow suggests a potential mechanism for the adjustment of work based on regular interactions.

3.4.2 Qualitative Insights on Quantitative Parameterization

The experiences and perspectives of street-level practitioners focus the quantitative inquiry on weeks and counties as the main units of analysis. Participants spoke mainly about the practice in their counties, focusing their thinking about changes in populations on that single county. Similarly, participants spoke of time mainly in the frame of the work week. While there were monthly meetings and feedback mechanisms, most of the concern was day-to-day and week-to-week scheduling. Weeks, then, are to be the focus of the quantitative inquiry. The reason that I did not select the day as the temporal frame is that participants noted that there were certain concentrations of activity on single days within a week, and even where there was a single dependency court day in a week the emphasis of the conversation was on the work week as a whole. These qualitative reports help root this study in practice-relevant temporal and spatial units (Abbott, 2016; Tuma & Hannan, 1986). Additionally, because "the court drives our work" the qualitative investigation supports quantitative study placing out-of-home care and maltreatment court populations in the same system.

3.4.3 Qualitative Insights Outside of Quantitative Parameterization

While the main focus of this chapter was in refining the conceptualization of the heuristic models presented in Chapter 2, lengthy interviews with front-line workers did provide an opportunity for additional insights into the workings of two county-level child welfare systems in Washington State. The purpose of this section is to highlight several interesting themes that emerged in participant interviews outside of the narrow focus of this project.

One of the main themes of child welfare practice revealed in these interviews was the central importance of relationships between caseworkers, attorneys, and even judges. These relationships manifested themselves in talk about formal convenings, informal encounters in courtroom hallways, after work social gatherings, and expectations about regular phone and email communication. These features of child welfare practice were frequently emphasized by participants in all roles within out-of-home care and dependency courts. The relational aspect of practice was most frequently discussed in terms of an opportunity to troubleshoot work-related problems or to otherwise facilitate getting work done. In addition to direct discussions about relationships (especially if the relationship spans a number of years), participants also gave a deep sense of the routineness of checking in with colleagues—not in a reactive, but a proactive sense—to see how a particular parent or family is doing. Attorneys, in particular Assistant Attorneys General and parents' representatives, spoke about their desire to check in with caseworkers on a regular basis about cases in between hearings. There were also themes of trust and resilience that came out of discussions about relationships within the system. Participants indicated that they valued the opportunity to speak with people who have similar work demands and face similar situations in their work as an opportunity to decompress considering the demands of the work.

The demands of a child welfare job were also frequently discussed in the context of caseworker turnover and retention. Problems of caseworker turnover and retention have been frequently studied. This study provides some additional detail by describing some of the roles that dependency court attorneys see themselves playing in turnover and retention. Specifically, attorney participants described the difficulty of case management in moments of rapid caseworker churn, specifically contrasting this to some experienced members of the dependency court bar. Attorney participants also noted that they felt some responsibility to train or bring up to speed new caseworkers, which required their time and energy. It is also interesting to consider the possible interrelationship of caseworker retention and the relational aspect of child welfare practice described above.

Another present theme in many of the participant interviews was the importance of hard and soft judicial influence. Though it was clear from attorney and agency participants that within the courtroom a lot of effort was made to conform child welfare practice to the will of the judicial officer, the importance and the influence of the judicial role was not contained within the courtroom. Several participants discussed how judicial management of dependency cases extended beyond court hearings and into attempts to manage the broader system through the use of influence outside of the courtroom. The role of convener was a deliberate and frequent exercise of the power of judicial officers.

In addition to a complication of the role of the judicial officer, participants in this study revealed the different roles that are played by the attorneys in dependency court. By "roles" I mean not just the ways in which attorneys represent different categories of participants in dependency court, but also in terms of their functions in other aspects of the system. For example, several participants noted the role that Assistant Attorneys General and parents' representatives played in keeping caseworkers on task, ensuring that service plans were being followed, and asking for accountability about the level of parental engagement. Attorneys, in particular Assistant Attorneys General and parents' representatives, spoke about their desire to check in with case workers on a regular basis about cases in between hearings. Some parents' representatives framed these topics as not wanting to be surprised at hearings or as keeping track of their clients. However, the work that parents' representatives (and Assistant Attorneys General) put in to cases in between court hearings may act as an additional layer of quality control within the child welfare system which may not be apparent if the focus is simply on actions in dependency court in and around hearings. In other words, the work of these active attorney participants may result in a different look to cases that appear before judicial officers.

3.4.4 Summary

The heuristic presented in Chapter 2 illustrates a way of conceiving of one type of structure in child welfare practice—that is, population structure created by entry and exit dynamics and bounded by capacity and responsive to feedback mechanisms which govern the system. This chapter provided a reality check for that conception. The conditions which could produce this kind of behavior are explicitly present in the subject dependency courts and out-of-home care systems. More specifically, we see that street-level practitioners think about populations and caseloads; talk to other practitioners, formally and informally, about those populations and caseloads; and respond to population and caseload fluctuations. Entries and case openings are events which serve as a salient population indicator, along with overall perceived workload and caseload. Practitioners focus mainly on day-to-day and week-to-week population indicators within their own counties of practice, and daily practice is shaped in terms of the caseload and workload on that day and in days directly proximate.

This chapter provides some evidence of the utility of thinking about child welfare populations in terms of a dynamic partial adjustment model. The following chapters will attempt to quantitatively justify the population as empirical subject.

Chapter 4
Quantitative Analysis: Data and Description

This chapter proceeds in two parts. The first part is a description of the out-of-home care and court data sets used in this dissertation. The second part describes the data.

4.1 Quantitative Data

The quantitative data for this dissertation was drawn from two administrative data sets from Washington State. Washington State has a child population of approximately 1.5 million. Each year, the Children's Administration receives approximately 70,000 reports of child maltreatment[1] and investigates about 32,000 of those reports. Approximately 6,500 unique children receive some response that might include judicial supervision or placement into out-of-home care each year (US HHS, 2015; 2013; 2012; 2011; 2010; 2009; 2008; 2007; 2006; 2005; 2004; 2003; 2002; 2001). Between 2004 and 2014, Washington State averaged an out-of-home care population of approximately 10,000 children per year, with approximately 6,000 children entering and 6,000 children leaving that population annually (US HHS, 2014a; 2014b; 2014c).

This dissertation focuses on a sample of six Washington counties: Clark, King, Pierce, Snohomish, Spokane, and Yakima. Together, these six counties represent approximately sixty percent of the total weekly average number of children in out-of-home care in Washington State. Most importantly, however, these counties provided the aggregate volume of court and out-of-home care cases that could allow for analysis at the weekly level—ranging from a weekly average of 1922 children in out-of-home care and 2139 open court cases in King County to 550 children in out-of-home care and 525 open court cases in Yakima County. Week-level analysis was limited or impossible in other counties due to small population sizes.

[1] Multiple reports could be received for one child.

4.1.1 Data Sources

Primary data for this dissertation comes from two sources: (1) Out-of-home care data collected by the Children's Administration and held by the Chapin Hall Multistate Foster Care Data Archive (hereafter "FCDA"); and (2) court case data collected by the Washington State Administrative Office of the Courts and held by the Center for Court Research. Both data sets were truncated to begin on January 1, 2000 and end on December 31, 2014, representing 5479 day-level records. Those data sets are discussed in turn.

4.1.1.1 Out-of-Home Care Data

The Children's Administration collects event-level data on individual children to track child welfare care spells. A care spell represents the amount of time a child spends in out-of-home care, and is marked by a start date, or entry, and an end date, or exit. The recording of these events is date and location specific. Thus, day- and county-level events can be aggregated from the individual-level records. That data is held, on behalf of the Children's Administration, by the FCDA, a data warehouse maintained by the Center for State Child Welfare Data and Chapin Hall at the University of Chicago. The FCDA contains fine-grained data for individual children and their experiences within the child welfare system, including details about out-of-home care spells.

The Children's Administration data set for this study comprises three variables: (1) out-of-home care entries, or placements; (2) out-of-home care exits, or terminations of out-of-home-care status;[2] and (3) total aggregate census by county. The entry/exit structure of this data set lends itself to population dynamics analyses which examine the growth and decline of populations based on births and deaths with that population (Wulczyn, 1996). The data provided

[2] These terminations of out-of-home care status include several different kinds of resolutions, including, but not limited to, return to the home of a parent or legal guardian; adoption or guardianship; or aging out of out-of-home care.

for this study was deidentified and in aggregate—by day, by county. Thus, for example, the data reports that on November 18, 2002, that there were three out-of-home care entries and two out-of-home care exits in Snohomish County.

Visual inspection of the out-of-home care dataset indicated that there were two outlying data points which occurred on Saturday, February 28, 2009 and Sunday, March 1, 2009. Personal communication with the Children's Administration indicated that there was a database conversion over that weekend, which may have created those errors. Additionally, because of the conversion the real values for those dates were unknown. The outlying values on those two dates were replaced by taking the mean values of similar days in February and March 2009. Saturday, February 28, 2009 values were replaced with the mean values of the eight surrounding Saturdays. Sunday, March 1, 2009 values were replaced with the mean values of the eight surrounding Sundays.

4.1.1.2 Dependency Court Data

Like the Children's Administration, the Administrative Office of the Courts collects event-level data to record the progress of individual court cases. These records form an official court docket, and the events are associated with dates and courts. Similar to out-of-home care entries and exits, the court event data records case openings and case closings. Case openings are defined by the filing of dependency petitions, and case closings are defined by the entry of an order closing the case. This docket data is held by the Center for Court Research, and was provided for this study deidentified and in aggregate—by day, by county. So, similar to the Children's Administration data, the court data reports that on November 18, 2002, that there was one petition filed, entry or case opening, and no cases closed in Snohomish County.

Unlike the out-of-home care data, a daily census of open court cases is not straightforward. Reports of beginning-of-year and end-of-year caseloads are available, but do not reconcile from year-to-year when considering day-level entries and exits. There are many reasons for this, including cases which remain on the docket even though they are closed, cases transferred out to or in from other jurisdictions, and other court-level recordkeeping errors. This year-to-year difference can be off as much as five percent of the total population. For this reason, I treat the calculated total aggregated population counts with some skepticism, and have instead focused analysis on the daily entry and exit counts.

4.1.2 Data Integration, Variables, and Aggregation

The out-of-home care data and the court data were merged by date, and organized by county. The county-level organization was supported by the qualitative findings of Chapter 3, and based on those findings higher-levels of geographic aggregation were not considered. The initial data file comprised four variables in each of the six counties as follows:

- **FE** – Out-of-home care entries
- **FR** – Out-of-home care exits
- **CF** – Court entries defined by dependency petition filings
- **CD** – Court exits, defined by orders to close cases

Based on the qualitative interviews reported in Chapter 3, *supra*, the data was further aggregated at the week level in order to represent the time horizon of perceived aggregate caseload, or, more specifically, the week-to-week scheduling and pace of street-level work. The decision to aggregate populations at the week level is related to this dissertation's purpose of exploring dynamics at a level most proximate to children in care and the professionals who serve them. Dynamics may exist at other levels of temporal aggregation (monthly, quarterly, or yearly, for example), but I believe those dynamics to be driven by other factors existing with greater impact at higher ecological levels—such as, for example, staffing cycles, organizational budget cycles, or state or national policy changes. The weekly aggregation produces a time series of 782 individual weeks.

Four additional variables were constructed to provide other population dynamics insights around system capacity and equilibrium. Specifically, a volume variable was created summing the entries and exits (or openings and closings) for a given date or date range; and a change in population size variable was created subtracting the exits from the entries (or the closings from the openings) to produce a net measure for a given date or date range. Those addition four variables in each of the six counties are as follows:

1 **Fvol** – Representing the total volume of out-of-home care case entries or exits during a given time period.

2 **Fdelta** – Representing the net volume of out-of-home care case entries or exits during a given time period.

3 **Cvol** – Representing the total volume of court cases opened or closed during a given time period.

4 **Cdelta** – Representing the net volume of court care cases opened or closed during a given time period.

Thus, for Snohomish County in the week containing November 18, 2002, there were an aggregated total of nine out-of-home care entries, nine out-of-home care exits, four court case openings, and two court case closures. Additionally, the overall out-of-home care volume was eighteen cases, the out-of-home care delta was a net of zero cases, the court volume was six cases, and the court delta was a positive net of two cases.

4.1.3 Advantages of Data Set

Several features of the Washington child welfare system and its relationship to the court system are notable. The primary among those is that these data are census data, that is, every administrative record for the subject counties is contained within the data set. This lack of sampling provides a precise view of the population dynamics that is only limited by the accuracy of administrative record keeping.

As described in Chapter 1, Washington has a high degree of centralized, state-level management influence on both the administrative and court procedures as compared to states with more decentralized systems. This may be important in reducing the amount of county-level variability that a state with a more decentralized system may experience. The Children's Administration is a state-level agency responsible for the management of all out-of-home care cases in Washington, and cases are not delegated to subcontractors. On the legal side, court cases are initiated by the state-level Washington State OAG. As opposed to county-level management, this state-level administration of several different key agencies may serve to reduce the level of between-county practice variation; or focus the majority of county-level practice variation on participants with little or no state-level connections—these include primarily judges and child representatives.

Moreover, in Washington there is also a tight linkage between placement in out-of-home care systems and openings of court cases. This is a result of a policy position that is reluctant to take on court supervision of intact cases. However, there are some cases which appear in the out-of-home care system, but not in the court system. These placements, either voluntary placements or short-term placements, may act to add some variation in an otherwise coupled system (Courtney & Hook, 2012). As a whole, however, the number of entries into out-of-home care

(**FE**) and the number of cases being opened in dependency court (**CF**) should show linkages across time.

4.1.4 Limitations of Data Set

While both the administrative child welfare and court system provides reliable out-of-home care entries, out-of-home care exits, court filings, and court case closings data at the daily level, there are some difficulties in using those events to reconstruct whole population size at the daily level. This is a consequence of within-state transfers of cases in both subsystems, for which records are kept in different event categories, and of record-keeping lags in the court subsystem, particularly for dependency case dismissal. This creates a situation where daily population estimates in the court subsystem can be off as much as five to seven percent and in the out-of-home care subsystem can skew by three to four percent when reconstructed based on annual census data. These discrepancies create unreliabilities in aggregate population analysis at fine-grained temporal levels—day and week—which argue against aggregate population analysis in this study.

A further limitation was a pair of database errors in the child welfare subsystem which occurred on Saturday, February 28, 2009 and Sunday, March 1, 2009. Errors, created in the process of a database conversion, produced nonsense values on those dates. Because these were weekend days—which tend to produce much lower volumes of work than week days—the nonsense entry and exit values on those days were replaced for analysis by taking the mean values of similar days in February and March 2009. Saturday, February 28, 2009 values were replaced with the mean values of the eight surrounding Saturdays. Sunday, March 1, 2009 values were replaced with the mean values of the eight surrounding Sundays.

Finally, these data all come from the State of Washington, thus limiting the generalizability of these findings.

4.2 Descriptive Analysis

Descriptive analyses were conducted in STATA and R in order to provide a picture of the structure of the time series. The descriptive analysis is broken down into two main approaches: Count-based approaches, which focus on raw numerical components of the time series; and frequency-based approaches, which focus on relational periodicity of the time series.

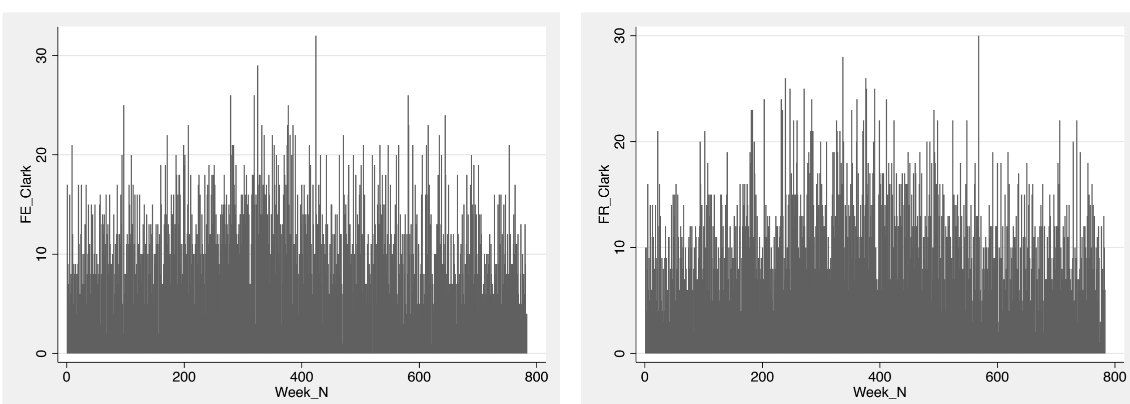
For the remainder of this dissertation, the reported figures will come from Clark County.[3] The data from the other five counties will be reported in the narrative, and, when necessary, comparison figures will be provided either within the text or in appendix.

4.2.1 Count-Based Analysis and Parameterization Techniques

Each individual outcome variable was evaluated by producing line or bar graphs of the time series over time, a series of summary statistics, and histograms representing value density.

4.2.1.1 Bar Graphs

Figure 4.1—Bar Graphs of Clark County Out-of-Home Care Entries and Exits



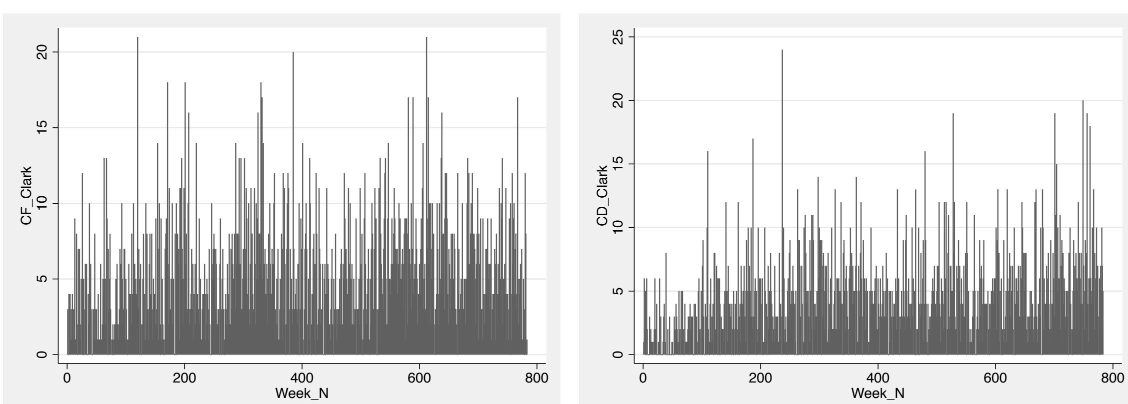
Counts of Clark County out-of-home care entries (right) and exits (left), by week, 2000–2014.

[3] Clark County was selected for the illustrative figures by random draw—because there are six counties in the study population, a single roll of a six-sided die was selected for randomization. That roll gave a value of 1, Clark County's alphabetical position within the sample counties.

The primary descriptive analysis technique employed in this study were graphical representations of the variables. Bar graph plots were employed to describe each of the above-described variables—entries and exits, total volume of entries and exits, and the net volume. Bar graphs were used instead of line graphs because these variables are not necessarily connected over time. Each bar represents the value of that variable for a given unit of time, total counts for entries and exits and total volume of entries and exits; and difference for net volume. Bar graphs were reported for the entire length of the time series, and were produced in STATA.

Figure 4.1 represents Clark County out-of-home care entries and exits, and Figure 4.2 represents Clark County dependency case openings and closings. In those plots, and in plots for each of the other counties, there were variations over time in the number of out-of-home care entries and exits and the numbers of dependency court case openings and closings. In Figures 4.1 and 4.2 we can see that the entries and openings rise to a consistently higher volume around week 300 (mid-year 2005) before tapering off slightly. We see a similar bulge and then falling action in the exits and closings series (mid-year 2007). From visual inspection, it is difficult to see any periodic patterning within the out-of-home care time series—that is, any cyclical peaks

Figure 4.2—Bar Graphs of Clark County Dependency Court Openings and Closings

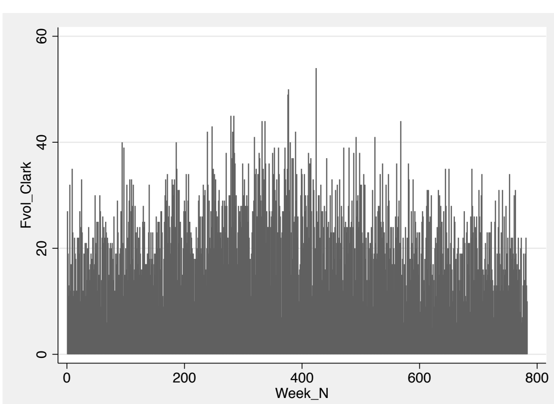


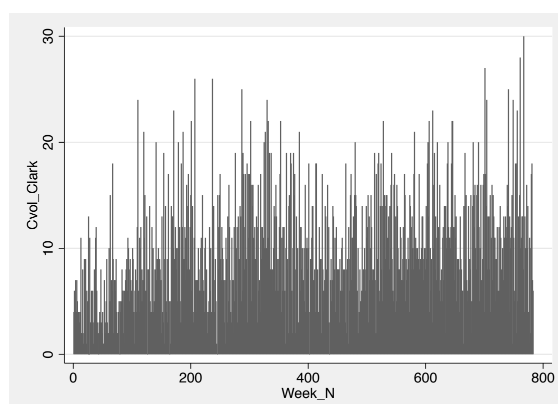
Counts of Clark County dependency court case openings (right) and closings (left) and valleys in the series are not clearly visible. The dependency court time series, on the other hand, feels a little more periodic, with noticeable and regular dips that occur at the end and beginning of each year. Aside from macro trends, Figures 4.1 and 4.2 indicate that there is a reasonable amount of apparent variability, week-to-week, in all of these series.

One distinguishing feature of these plots is that openings and closings occur at a much lower volume in dependency courts than they do in the out-of-home care systems. This runs counter to the idea of a tight linkage between out-of-home care placement and dependency case openings, and suggests that there is significant churn in the out-of-home care system that is not captured in the dependency court system. Given the aggregate nature of this data, it is not possible to pull out the churn of individual cases, but this is suggestive of the short-term placement patterning that was found by Courtney and Hook (2012).

In the other five counties, there are similar ebbs and flows over time, though peaks occur at different temporal points over the length of the series (for example, King County entries and court opening series shows peaks early in the time series (around 2002) and then at a similar peak again (around 2012); Pierce shows a more consistent volume throughout except for a peak

Figure 4.3—Bar Graphs of Case Volume in Clark County Out-of-Home Care and Dependency Court



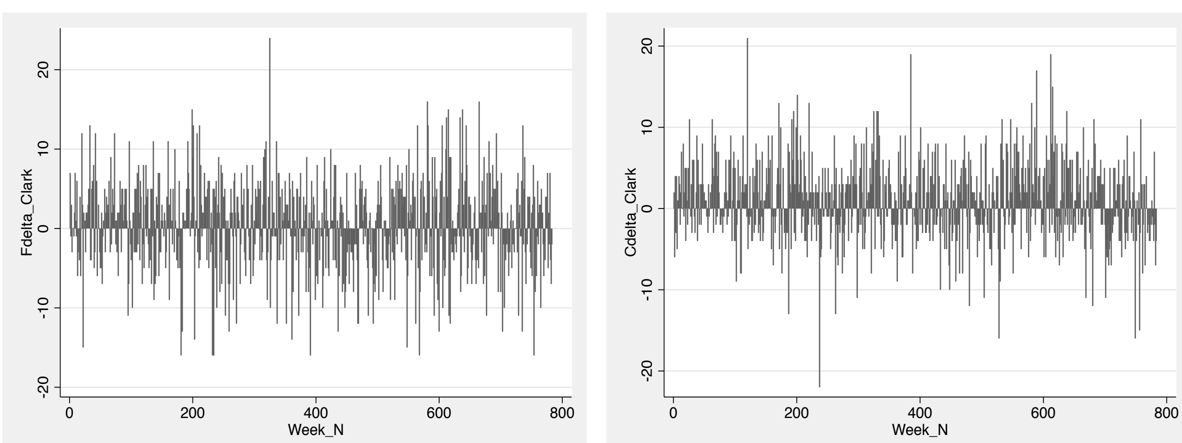


Counts of total sum of case openings plus case closings in out-of-home care (right) and dependency court (left).

(in 2009) and then a valley immediately following (in 2010)). All time series show a high degree of week-to-week variability, similar to that within the Clark County series; and a lack of apparent periodicity in out-of-home care, with the same seasonal drop around December and January in dependency court case openings and closings. Similarly, all counties show fewer case openings and closings in the dependency court system than in the out-of-home care system.

The total volume of case openings and closings in both out-of-home care and in dependency court are represented in Figure 4.3. Overall, the total volume displays different trends than either of the component parts that make up those volumes (entries plus exits in the case of out-of-home care, and case openings and closings in the case of dependency court). In the case of out-of-home care volume Clark County, and the other counties, display flatter volume graphs, with peaks and valleys that move more gradually than in either the entry or exit series. On the other hand, dependency court volume in Clark County, similar to the other counties) gives a visual appearance of more up and down movement when compared to the out-of-home care series, though the end/beginning of the year trend is less apparent in the summed series.

Figure 4.4—Bar Graphs of Change in Volume in Clark County Out-of-Home Care and Dependency Court



Change in the total population of cases (entries minus exits, or openings minus closings) in out-of-home care (right) and dependency court (left).

Finally, Figure 4.4 represents the difference between out-of-home care placements and exits, and dependency court case openings and closings. These plots show the aggregate change in the out-of-home care or dependency court population within a given week. In Clark County and in other counties these change plots are highly variable and indicate regular switching behavior. In Clark County, most weeks group within the +5 to -5 cases range, and it appears to be rare within these charts to have several consecutive weeks of high or low values. The exception to that switching rule is 2011 in Clark County, where there appeared to be a cluster of consecutive weeks of high entry values. Comparing Figure 4.4 to Figures 4.1 and 4.2, it appears that this cluster can be explained by a lower than average number of returns home in out-of-home care and a lower than average number of case closings in dependency court during that time. These patterns are repeated in other counties, where change in case volume clumps around near-zero values, and tends to appear to rapidly switch between high and low values in nearby weeks.

In general, the bar graphs indicate high week-to-week variability, some indication of trends across the length of the time series (but no consistent trends across time series), little indication of periodicity on an annual level (in spite of slowdowns in volume in the last weeks and first weeks of each year in the court system). In the change plots, however, the switching behavior and near-zero tendency could provide some indication of equilibrium-type feedback behavior.

4.2.1.2 Summary Statistics

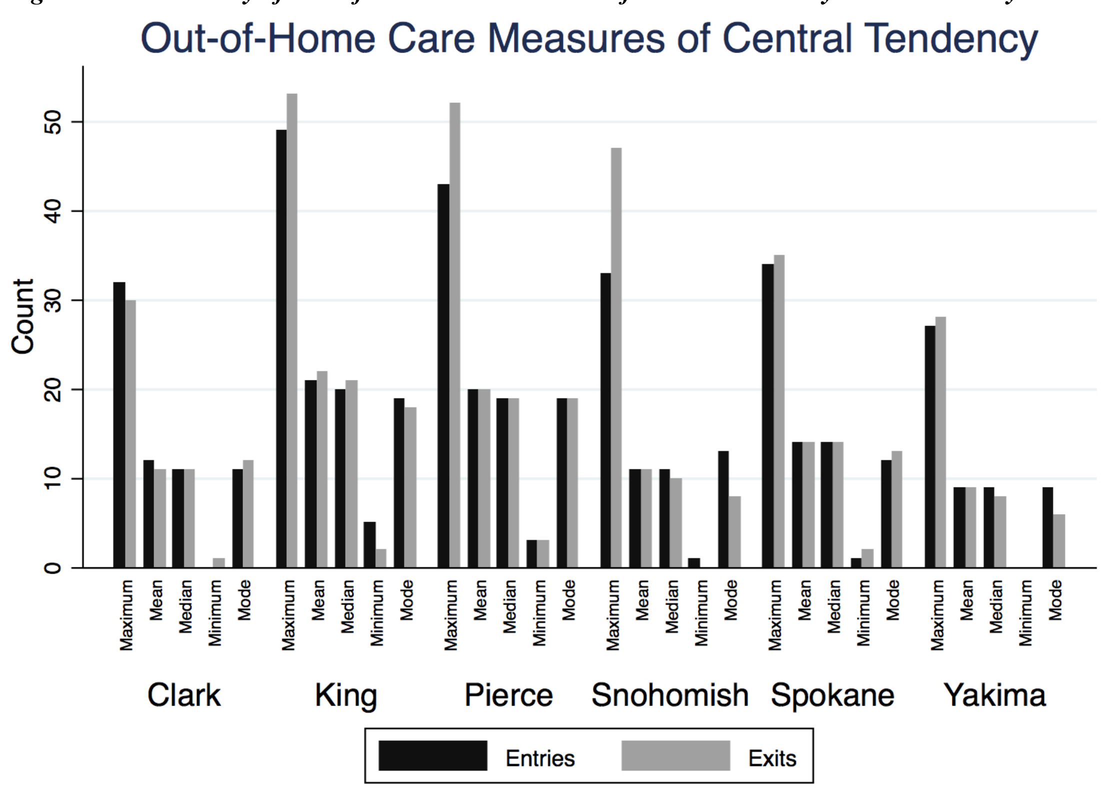
Additionally, for each variable six summary statistics were taken: mean, standard deviation, median, mode, minimum, and maximum. All of these summary statistics were reported for the length of the time series. All summary analysis was done using STATA. Table 4.1 provides these summary statistics for Clark County.[4]

Table 4.1—Summary Statistics for Out-of-Home Care and Dependency Court in Clark County

Clark County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	12	11	23	0	5	4	10	1
Std. Dev.	5	5	8	6	4	4	5	5
Median	11	11	22	0	5	4	9	1
Mode	11	12	19	0	3	4	8	-2
Minimum	0	1	5	-16	0	0	0	-22
Maximum	32	30	54	24	21	24	30	21

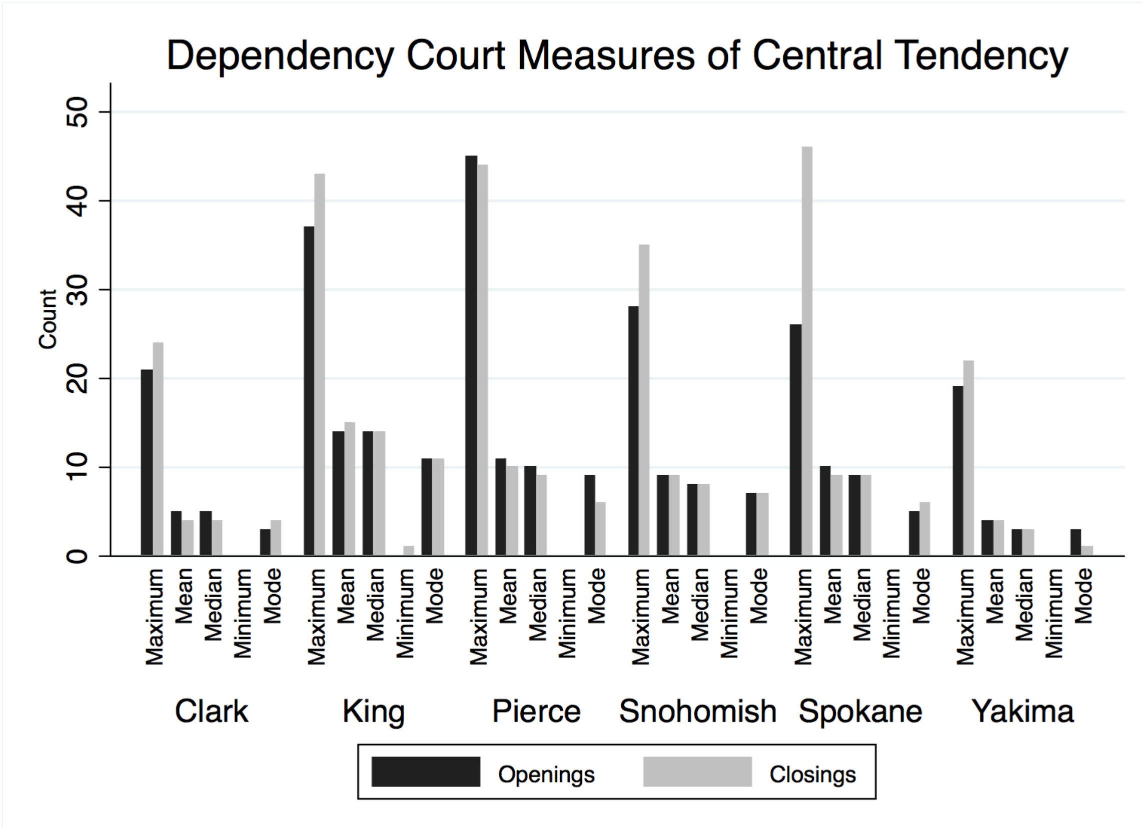
Figure 4.5—Summary of Out-of-Home Care Measure of Central Tendency in Clark County



This figure reports five measures, maximum, mean, median, minimum, and mode, for the out-of-home care subsystem in the six study counties. The counts are reported in number of children placed or returned from in out-of-home care per week.

[4] A table of summary statistics for the other five counties can be found in Appendix A.

Figure 4.6—Summary of Dependency Court Measures of Central Tendency in Clark County



This figure reports five measures, maximum, mean, median, minimum, and mode, for the dependency court subsystem in the six study counties. The counts are reported in number of cases filed or closed per week.

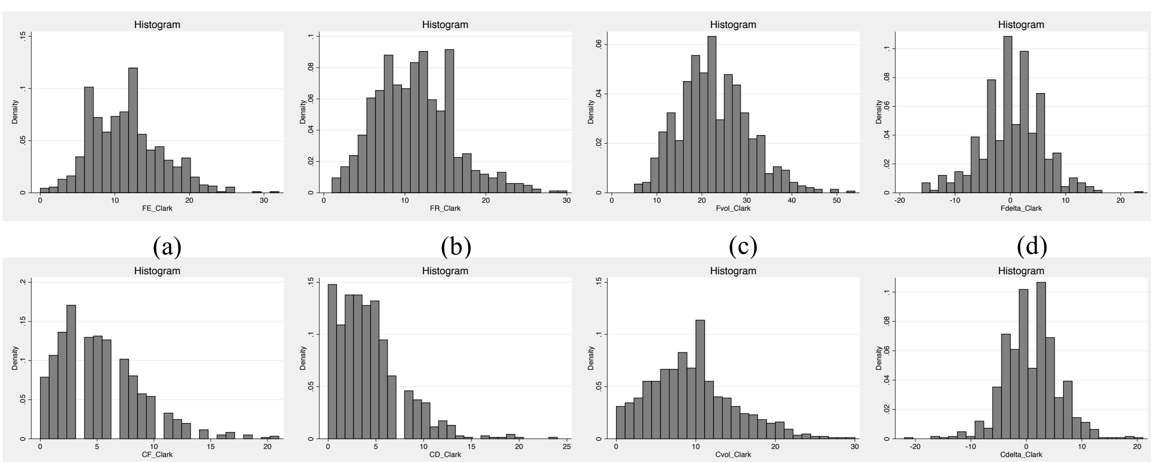
Notable in all time series is the near similarity of the measures of central tendency. Mean, median, and mode across all counties and all variables only deviate by two or three cases (if at all), with the maximum range being five (found in the Pierce County dependency court openings as the difference between mean and mode). This is an indication of the relative count stability of these series over time. Additionally notable is the delta values in all counties. The summary statistics in all delta time series indicate an affinity for zero and near zero values across the length of the series, reinforcing the appearance of the bar plots in Figure 4.4.

Figures 4.5 and 4.6 report summary statistics for the time series in each county, with Figure 4.5 representing the out-of-home care subsystem, and Figure 4.6 representing the dependency court subsystem.

4.2.1.3 Histograms

As a final count-based descriptive, histograms were generated for each variable. Histograms indicate the density of given variable values across the range of values in the time series. In addition to indicating the range and distribution of the variable values, histograms can indicate potential points of equilibrium if densities collect around certain values. Additionally, the modality of histograms can indicate trends or shifting baselines within the data. Histograms were produced in STATA.

Figure 4.7—Histograms of Weekly Densities for Out-of-Home Care and Dependency Courts



(e) (f) (g) (h)

Histograms representing the density of counts for variables. (a) Out-of-home care entries. (b) Out-of-home care exits. (c) Out-of-home care volume. (d) Out of home care delta. (e) Dependency court case filings. (f) Dependency court case closings. (g) Dependency court case volume. (h) Dependency court case delta.

There are several interesting aspects of the histograms. In the Clark County out-of-home care system, the large bulk of densities occurs in a fairly limited range for entries, exits, and volume. That is, Figure 4.7(a,b) indicates that the clear majority of weeks have entries and exits which number between seven and fifteen, with many fewer weeks with entry and exit numbers above and below that range. Additionally, the out of home care volume in Figure 4.7(c), where the densities occur in a large rising block in a range of fifteen to thirty-two total cases per week. These observations suggest that there might be structural forces which limit the range of out-of-home placements and exits within a work week. Conversely, the court subsystem in Figure 4.7(e–g) does not exhibit the same lower bound to that range. There are many more zero count weeks in the court subsystem, and the case openings and closings, while distributed, are spread more evenly across the range of possible values up to an upper bound around ten (it appears to be the rare week where there are more than ten case openings or closings) where we see tapering off in both the opening, (e), and closing, (f), distribution. Finally, in the difference variable (Figure 4.7(d,h)) we can see, as expected from the descriptive statistics, that there are large peaks in zero and near-zero values for the intra-week difference between case openings and closings.

With the exception of King County, discussed in more depth below, the other four counties in the sample show similar "shapes" in their histograms as those in Clark County (with differences in plateau values). King County differs in that its out-of-home care and court entries/openings and exits/closings are similarly normal looking distributions. King County's court subsystem has a smaller density of zero and near-zero weeks for both case openings and case closings. This suggests that in the King County court subsystem, like in the out-of-home care subsystems in King and the other five counties, there is some upper and lower bound preference for the number of cases that are handled in a given week. The King County histograms for the difference between case openings and closings was a similar curve with a high proportion of zero and near zero values.

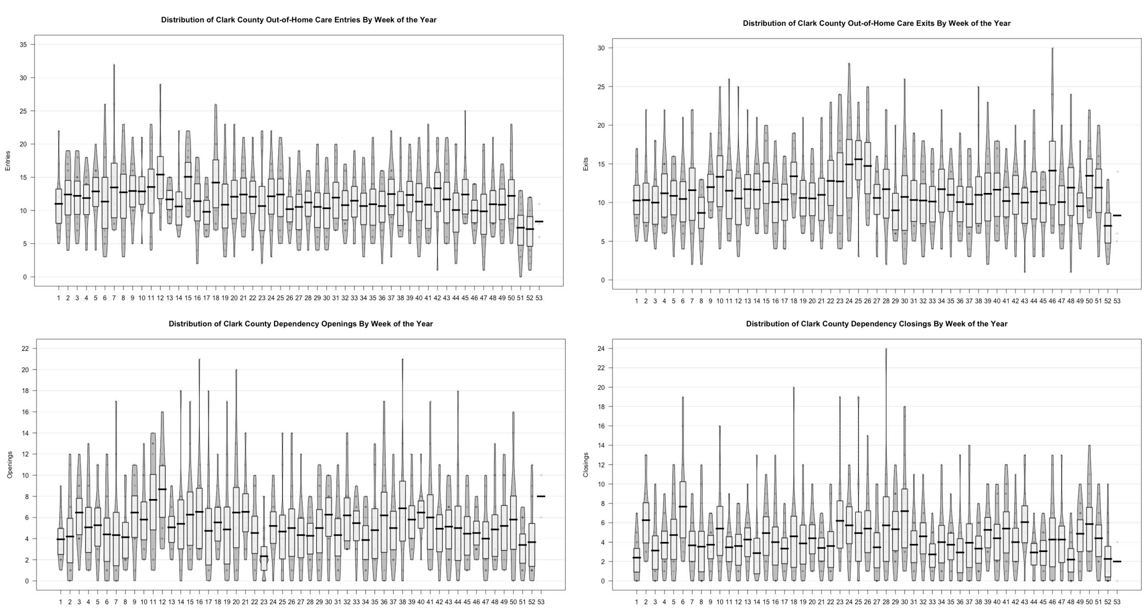
4.2.2 Frequency-Based Analysis and Parameterization Techniques

Each individual outcome variable was evaluated using the following frequency-based methods: Seasonal decomposition, stationarity tests, Hurst exponents, and periodograms.

4.2.2.1 Seasonal Decomposition

A first attempt to understand seasonal fluctuations of the time series was made using RDI plotting. The RDI plot was created by plotting the number of cases for each week of the year over the course of the time series. Arranging the time series by week of the year provides insight into systematic seasonal fluctuations over the length of the time series by indicating times of the year where either more or fewer events occur than other times of the year. Figure 4.8 represents that plot for Clark County. Figure 4.9 represents that plot for all six counties in the sample. Repeating the process for both individual counties and aggregated counties within the sample provides some window into how local practice might differ from more systematic seasonality.

Figure 4.8—Weekly Case Density in Clark County Out-of-Home Care and Dependency Courts

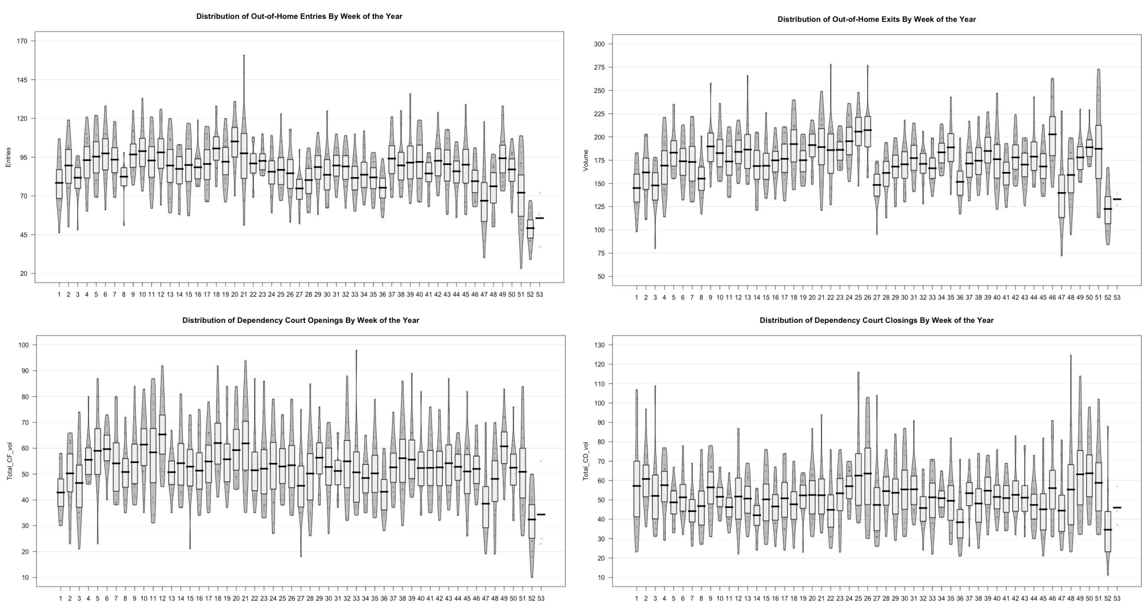


RDI plots for out-of-home care entries (upper left), exits (upper right), dependency court case openings (lower left), and closings (lower right) showing average densities and range of values by week.

RDI plotting illustrates raw data, descriptive information (including mean and range), and an inferential statistic (smoothed densities, and highest density intervals). RDI plots roughly resemble box plots, but display slightly different information. The range and the mean are displayed, but the density statistics require elaboration. Bayesian highest density intervals are defined as those intervals in which points lying within the interval have a higher probability density than those points that lie outside of that interval. The highest density intervals are represented by the box on the plot which represent a 95% confidence interval of the range of the highest density interval. This analysis was performed using the R package {yarrr}.

In all RDI plots in Figure 4.8 we can see that the week of Christmas (week 52) tends to be among the lowest case volumes of the year for Clark County—and in both the out-of-home care entries and court openings series, the week before Christmas joins that week in relatively low volume. Other holidays, including Memorial Day (around week 26), the Fourth of July

Figure 4.9—Weekly Case Density in Out-of-Home Care and Dependency Courts



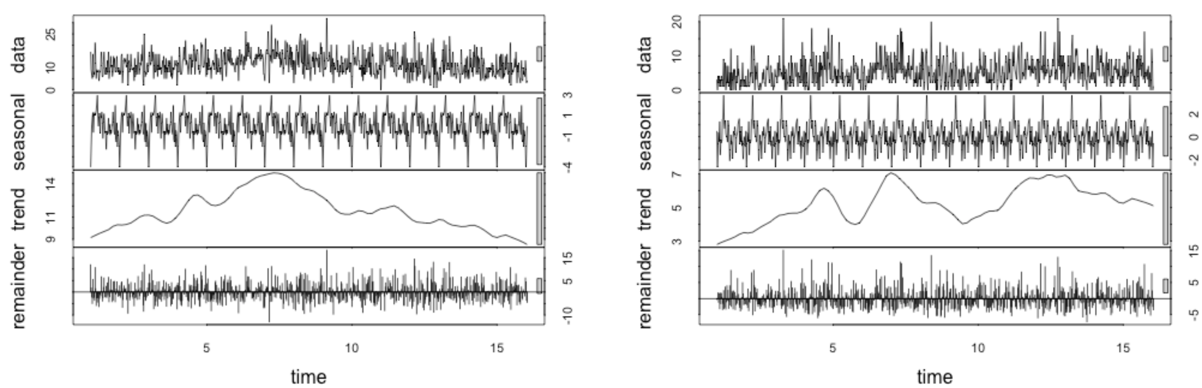
RDI plots for aggregated out-of-home care entries (upper left), exits (upper right), dependency court case openings (lower left), and closings (lower right) showing average densities and range of values by week for the six sample counties.

(around week 27), and Thanksgiving (around week 48), are not as visible in the series as the Christmas holiday. There are also increases in both out-of-home care placements and court case openings in March. There are increases in out-of-home care case closings and court case closings in June. In November and December there are bumps in out-of-home care exits. The rest of the weeks in the year, it appears that these time series operate within a relatively narrow range (as suggested by the histogram analysis in Section 4.2.1.3).

Figure 4.9 displays the same RDI plots with data from all six sampled counties. Other than the December slowdown, we can see that the week-to-week variation in these plots is greatly smoothed in aggregate when compared to Clark County (Figure 3.7) alone. Unlike the Clark County plots, the aggregate plots show a more punctuated slow down during weeks where holidays typically fall, and, interestingly, an increase in overall work in the week or weeks immediately preceding a holiday. Similar to the Clark County plots, however, weeks that do not contain a holiday or immediately surround a holiday seem to fall in a fairly consistent range across the whole year with the exception of higher than average out-of-home care exits during the month of June. Overall, the RDI plots suggest that there is weak seasonality over the annual length of these time series (with the exception of the slowdown in the last weeks of December).

Nevertheless, I next preformed a seasonal decomposition analysis to get a finer-grained look at seasonal patterning. Seasonal decomposition deconstructs a time series into three separate components: a seasonal oscillation, an overall trend, and remainder values. These individual components provide insight into structure within the time series which can accounted for in analysis and modeling. The data in this study was analyzed using a forced annual period. Seasonal loess smoothing is done by taking the mean of each periodic value set to find the seasonal component. Similarly, trend loess smoothing takes the mean of each periodic value after the seasonal component was removed. The remainder reports the residuals from seasonal plus trend fit. These values are for each component trend. This analysis was performed using the R package {stats}.

Figure 4.10—Seasonal Decomposition in Out-of-Home Care and Dependency Courts Entries Time Series



(a) (b)

Seasonal decomposition plots for out-of-home care entries, (a), and dependency court case filings, (b), showing the observed time series (top panel), the seasonal component (second panel), the loess smoothed trend after removing the seasonal component (third panel), and the remaining difference between the observed data after accounting for the seasonal periodicity and trend components of the time series (bottom panel).

The findings of the seasonal decomposition for two representative Clark County time series are represented in Figure 4.10. Similar to the observations in the RDI plots discussed above, the seasonal component plots indicate a lower limit in January and February. The seasonality is forced annually, and we see upper limits in April and May, falling through the summer to August, rising again through the beginning of November and then falling into the end of the year. Though the week-to-week details of the plots for courts and out-of-home care systems vary by county (the peaks and the valleys move around a little in May/June, August/September), the overall shape of the seasonal patterning is similar. Similar as well, however, is the remaining component within the analysis. These remainders represent 15–50% of the variation within the observed time series across all counties. This suggests the possibility that the real driver of the forced seasonality observed in the second panel of Figure 4.10 is the relatively slow period surrounding the Christmas/New Year's holiday, and that the periodic seasonal analysis is simply bending to accommodate those points. This large remainder in the seasonal decomposition analysis, combined with the picture of a relatively stable annual time series presented in the RDI plots, limits the utility of attempting to model seasonality in these weekly time series.

4.2.2.2 Tests of Stationarity

Whether a time series is stationary or nonstationary can determine the appropriate analytical techniques. A stationary time series is one in which the mean and the variance are relatively consistent across time. A nonstationary time series, on the other hand, could possess patterning dominated by (or influenced by) the presence of a unit root. A unit root, present in nonstationary time series, can be thought of as a component of a time series which systematically changes over time. The presence of a unit root in a time series can disrupt statistical analysis of time series models that do not account for it, and thus a time series which contains a unit root must be differenced in order to comply with the assumptions of commonly used statistical tests Unit root tests in general have low statistical power, and multiple tests are necessary to ensure checks on that low statistical power (See Zivot & Wang, 2006).

Two unit root measures are used in this study: The Augmented Dickey-Fuller test (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS). Because the data was inspected for exponential trends, with none being found, the data was not log transformed before performing these tests. The ADF test is a test which tests the hypothesis that a time series is difference stationary (a unit root) against the alternative hypothesis that the series is trend stationary.

Difference stationarity in a time series indicates that the mean trend is stochastic. Trend stationarity in a time series suggests that the mean trend is deterministic, that is that the time series can be expressed as a trend, plus a random walk and error. The ADF test estimates a regression of a time series with k lags (where k is set to $[(T-1)^{\frac{1}{3}}]$ where T is the length of the time series). Near zero ADF constants indicate that the time series may contain a unit root, and may require differencing. An ADF constant of less than zero indicates that a time series may be trend stationary.

The KPSS test tests the hypothesis that a time series is trend stationary. Thus, the KPSS test reverses the null and alternative hypotheses of the ADF test. That is, the null hypothesis for the KPSS test is that the time series is trend stationary, with the alternative being that the time series is difference stationary (a unit root). In the KPSS test near zero (that is, under 0.74 with a conservative .01 alpha)[5] constants indicate that a time series may be trend stationary, while nonzero numbers indicate the presence of a unit root.

Tests of stationarity were performed in R using the {tseries} package.

Table 4.2—Tests of Stationarity for Clark County time series

Clark County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
ADF	-5.74	-5.47	-5.06	-7.90	-6.73	-7.78	-6.71	-7.73
KPSS	0.62	0.70	0.74	0.10	0.14	0.26	0.24	0.11

All of the time series in the six sample counties indicated evidence of trend stationarity using the ADF and KPSS tests. This suggests that the time series in the sample do not require detrending before analysis. Though several series—including out-of-home care entries, exits, and

[5] A conservative alpha was chosen here because of the combination of the KPSS test with the ADF test.

volumes in Clark County—would have indicated the presence of a unit root using a less conservative KPSS test alpha (of, say, .05), those series were all found to be stationary using the ADF test. It is unsurprising that the delta values for the Clark County out-of-home care subsystem would indicate more trend stationarity in the KPSS test. One common method of detrending is differencing the time series, and though the delta calculation is not the same as a first-order differencing calculation, it is similar in that it is looking at the week-to-week change component of the time series. Table 4.2 reports the ADF and KPSS tests for Clark County time series.

4.2.2.3 Hurst Exponent

The Hurst exponent, *H*, is a statistic which assists in evaluating the long-term correlations and self-similarities within the fluctuations of values in a time series. The Hurst illuminates the long-range switching behavior of a time series in terms of the predictable dependence of that behavior. More specifically, the Hurst assists in differentiating anti-persistent, persistent and random time series (Keitt and Stanley, 1998). A persistent time series are those in which a high value is likely to be followed by a high value (and a low value by a low value). Anti-persistent time series are those in which a high value is likely to be followed by a low value (and a low value by a high value). Random time series, in the Hurst sense, are those where there is little predictive patterning of the switching behavior of a series.

There are various calculations used to estimate the Hurst. Eight different methods are employed here. The first six methods describe the persistence of the time series in the time domain. Time domain Hurst calculations all assess variability of time series by separating the series into groups, calculating the between-group variability, and predicting the Hurst by linear regression. Variability is assessed through analysis of rescaled series range (rescaled Hurst, corrected rescaled Hurst, empirical Hurst, and corrected empirical Hurst), variance (variance-based Hurst), and comparisons of group cumulative sums (Higuchi Hurst). The final two methods describe the persistence of the time series in the spectral domain. Determination of the Hurst in the spectral domain is based on two different applications (standard and smoothed) of the spectral density function (SDF), a semiparametric spectral estimation of density of signal at a specified frequency (see, generally, Rea, et al., 2009).

Hurst values of between 0 and 0.5 indicate an anti-persistent time series; values of between 0.5 and 1 indicate a persistent time series; values near 0.5 indicate randomness within the time series. Hurst values above one are not informative. The Hursts were calculated using the R packages {pracma} (for the rescaled Hurst, the corrected rescaled Hurst, the empirical Hurst, and the corrected empirical Hurst) and {fractal} (for variance-based Hurst, Higuchi Hurst, the standard and smoothed calculations based on the spectral density function).

For the sample counties, the out-of-home care entries, exits, volume, and the court subsystem openings, closings, and volume all indicate some degree of persistence, that is the Hurst values for those series is greater than 0.75. This means that the values of those series are relatively stable over time, not subject to patterned or random switching behavior, where values are generally expected to be similar to immediate past values. Interestingly, however, the delta time series across both subsystems in all counties tends to approach Hurst values of 0.5, indicating random switching behavior that can be either persistent or anti-persistent at different points within the time series—this suggests a more Brownian look to delta series. Example variance-based Hurst exponents for Clark County are provided in Table 4.3, with an average given on the top line or comparison purposes.

Table 4.3—Summary of Hurst Exponent Calculations for Clark County time series

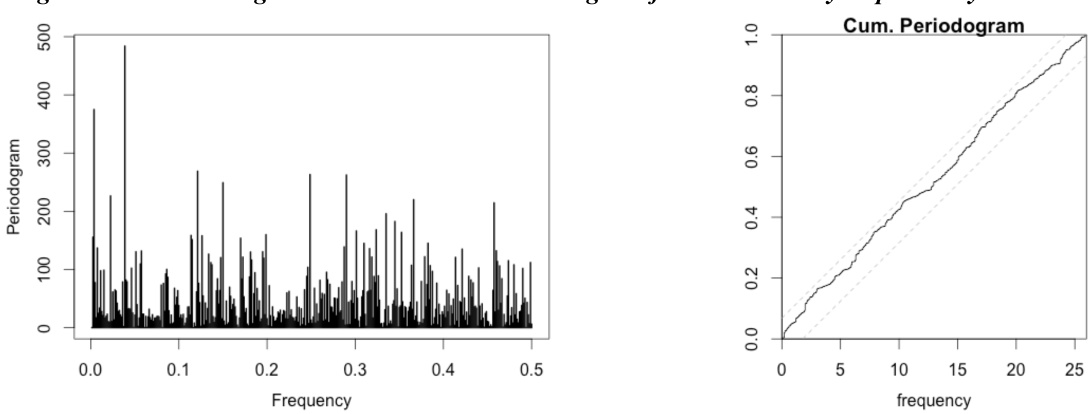
Clark County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Av. Hurst	0.8690	0.9288	0.9389	0.5711	0.8754	0.8754	0.8980	0.6594
R/S	0.7160	0.7394	0.7590	0.5488	0.6496	0.6794	0.7016	0.5629
Cor. R/S	0.8442	0.8934	0.9218	0.5921	0.7685	0.8248	0.8532	0.6458
Emp.	0.9290	1.0480	1.0522	0.5920	0.8752	0.9846	1.0123	0.7445
Cor. Emp.	0.8800	0.9973	1.0049	0.5493	0.8274	0.9262	0.9583	0.6980
Agg.Var.	0.8301	0.8764	0.8792	0.5962	0.7640	0.8290	0.8544	0.4344
Higuchi	1.0150	1.0180	1.0165	0.5484	1.0081	1.0083	1.0082	0.8709

4.2.2.4 Periodograms

Periodograms provide qualitative insight into the spectral composition of a time series. The raw periodogram assists in identifying dominant periods within a time series. In a purely random series, the periodogram will arrange itself randomly around some constant value.

Figure 4.11—Periodogram and Cumulative Periodogram for Clark County Dependency Court Delta



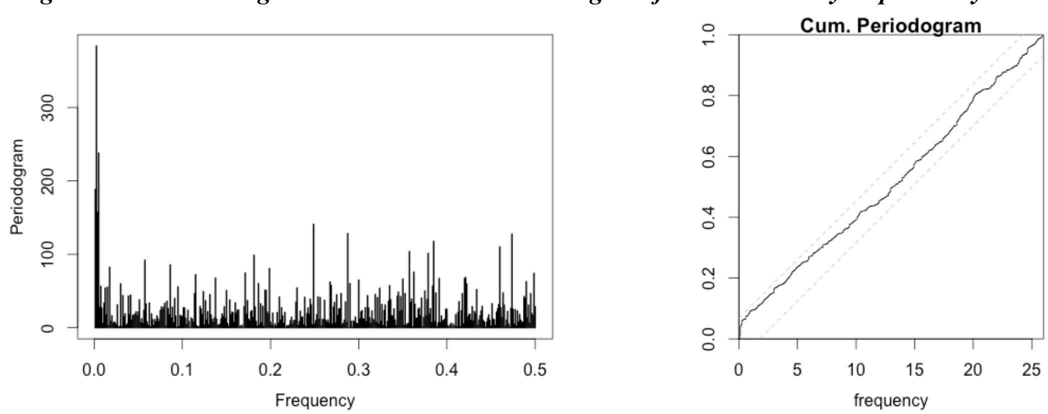
(a) (b)

Periodogram, (a), and Bartlett's cumulative periodogram, (b), for the difference in case openings and closings per week in Clark County. In (a), though there are two peaks in low range frequencies, there is a relatively consistent distribution of values across the frequency spectrum. In (b), we see that the accumulation of frequencies is roughly linear and does not fall outside of the confidence intervals.

Periodograms with dominant values in lower frequencies may indicate that there are long-period linear trends in the time series. Periodograms with dominant values in the upper frequencies indicate that there are short-term linear trends within the time series. A further way of assessing the randomness of frequency of a time series is to use a Bartlett's cumulative periodogram. In a Bartlett's cumulative periodogram, period density is plotted against frequency. A time series which displays no dominant periods or patterning will fall within confidence intervals of a line with a slope of one which intersects (0,0) on the plot. Both periodogram plots were produced using the R {stats} package.

For the delta series in both courts and out-of-home care in all counties, periodograms and cumulative periodograms indicated fairly random distributions of values across frequency and no dominant periods. An example of this is given in Figure 4.11, which presents the Clark County dependency court delta. For the sample counties, the out-of-home care entries, exits, volume, and the court subsystem openings, closings, and volume all tend to indicate some slight evidence of long-term trend patterning. An example of this is given in Figure 4.12 which presents Clark County dependency court case openings. The strength of this long-term trend patterning is

Figure 4.12—Periodogram and Cumulative Periodogram for Clark County Dependency Court Closings



(a) (b)

Periodogram, (a), and Bartlett's cumulative periodogram, (b), for the case closings per week in Clark County. In (a), there are two very high low frequency values. In (b), we see those low frequency values brushing against the confidence intervals in the lower range.

relatively weak but notable across series and subsystems. Though the details of each series differ in the periodograms and cumulative periodograms, similar trends to the example series are present throughout the subsystems in the sample counties.

4.3 Conclusion

What picture is presented by analysis of the week-level time series describing the out-of-home care and court subsystems in the six sample counties?

With the exception of the delta time series—the series representing entries/openings minus exits/closings within a given week—the series all display high variability within a relatively narrow set of bounds that vary on the county level. That is to say that most weeks in the time series have a relatively consistent number of entries and exits into out-of-home care or openings and closings in dependency court. The lower bounds of court subsystem activity tends to be at zero, when compared to out-of-home care where almost all weeks have some entries and exits. In the dependency court subsystem, almost all weeks have some entries or exits, but, unlike the out-of-home care subsystem, there are lots of weeks that do not have a case opening or that do not have a case closing. This is, perhaps, because the court systems tend to operate an overall lower volume than the out of home care systems. Overall, in fact, across all comparable time series, out-of-home care systems operated at about one and a half times the weekly volume of the dependency court system.

The delta time series provided an exception to some of the above. These values tended to accumulate around zero in all time series in both the out-of-home care and dependency court subsystems. This suggests that the typical week in out-of-home care has either a balance or a near balance in the number of entries and exits (with a similar finding in the dependency court data). This could be due to coincidental workflow effects, coincidental due to the regularization of population processes,[6] or it could be some evidence of an equilibrium preference within the system (or some combination of those three alternative explanations).

Within the data there is little evidence of systematic patterning across several analyses. What seasonality there is might be explained by a consistent annual slowdown in the Christmas/New Year's time period, and the increase in activities (especially exit/closing activities) in May and June. However, most weeks of the year appear to be similar to most other weeks of the year. Similarly, the time series are trend stationary, persistent—with the exception of the delta series which tend toward random switching behavior—and lacking in strongly indicated dominant periods. In general, this linear analysis of the time series suggests that a moving average and random walk may best describe the series.[7] Because this study focuses on the possibility of resource constraints in the child welfare system producing nonrandom behavior in population time series, we will turn to other approaches in Chapter 5.

[6] That is, for example, if the exit times for entries are normally distributed, and entries are relatively evenly distributed across the time series then we would expect that any given exit week would have a similar number of entries to the aggregate number of exits.

[7] See Section 2.1.4.

Chapter 5
Quantitative Analysis: Method

The descriptive data analysis done in Chapter 4 suggests that the out-of-home care and dependency court time series that are the subject of this dissertation have weak systematic patterning on the linear scale. The purpose of the remainder of this dissertation is look for nonrandomness within those weakly coupled systems. The approach described in this chapter has both linear and nonlinear components. Whereas the qualitative portion of this dissertation (described in Chapter 3) shades toward the positivistic, the quantitative analysis described here incorporates interpretive elements. The statistical tests employed are not solely intended to assess the practical and statistical significance of a pre-defined model, but instead the model, the theory, and the statistical method are used to craft a rigorous, empirically-validated story about the data within the population dynamics frame (Babones, 2015).

The first part of this chapter describes the process through which lag lengths were set in this analysis. The second part of this chapter describes an approach to weakly-coupled, lagged deterministic systems called EDM. There are two principle methods contained within EDM which will speak directly to the hypotheses in this dissertation. Simplex projection will provide a test of predictable nonrandom behavior across time lags in univariate systems (e.g., out-of-home care entries). That is, simplex projection is a method to determine the strength of the links between a past number of entries and the present number of entries. This speaks to the first hypothesis. Convergent cross mapping (hereinafter, “CCM”)will provide a test of predictable nonrandom behavior in bivariate systems (e.g., the relationship of out-of-home care entries to out-of-home care exits, or the relationship of out-of-home care entries to dependency court case filings). In other words, CCM will address the question of the strength of the coupling between the past number of exits and the present number of entries. This speaks to both the first hypothesis (testing intrasystem dynamics—relationships with the out-of-home care system or dependency court system) and the second hypothesis (testing intersystem dynamics—relationships between the out-of-home care and dependency court systems).

5.1 Lag Determination

Time series analysis, and in particular nonlinear analysis, is highly sensitive to time lags, or tau values (τ). Thus, defining the appropriate tau, or lag structure, of the time series is critically important. Statistical methods used in this study, further described below, focus mainly on bivariate lag relationships in single variable systems where the lag values are determined by examining that variable's relationship with itself across a fixed lag length. Therefore, the primary goal in determining lags is to identify lag times where we see the most substantial bivariate relationships. Looking for these regular couplings across time allows us to hopefully identify significant stimulus-response patterns within the time series.

As discussed in Chapter 2, time lag is a proxy for organizational feedback and response mechanisms which may impose structural constraints on child welfare practice. That is, how long does it take the child welfare system to absorb information about the number of entries and then react by making an adjustment in some future week. Moreover, because these feedback and response mechanisms might vary by outcome variable and county, lags must be determined for each outcome variable. Lags, then, are outcome variable specific, and in later analysis the predictor variables are tuned to the empirically determined lags of the outcome variable. Additionally, as there are no theoretical bases for lag selection, lags must be determined empirically. The qualitative interviews described in Chapter 3 suggest, however, some practical bounds for feedback and responsive mechanisms due to the horizon of perception that ranges up to a month or a little longer. Because of this horizon of perception and the focus of this dissertation on fine-grained temporal dynamics, the lag analysis focuses specifically on lag lengths of up to ten weeks. But the problem of identifying spurious correlation or correlations which are driven by synchronous population behavior are not insignificant here. To avoid selecting on the dependent variable—that is saying that the best lag is simply the most correlated lag—multiple approaches are used. As results for EDM are discussed in Chapter 7, I will present examples using alternative lag times to illustrate post-hoc alternatives. But the attempt here is not to look for the most compelling EDM results across lags, but to attempt to determine a lag a priori and stick to that lag through further analyses.

The first set of methods used to investigate lag length relate to the autocorrelation between bivariate lags. Patterning is observed where there are stronger relationships between a variable and a particular past observation of that variable, as determined by higher autocorrelations. For example, if entries are more correlated with observed entries from five weeks ago than they are with observed entries from seven weeks ago, then we have reason to think that it may take five weeks for the child welfare system to absorb information about entries and the react to that stimulus. In this study, autocorrelation was evaluated computationally and graphically. First, STATA was used to generate autocorrelation and partial autocorrelation calculations for each variable and its lags. Then those autocorrelations and partial autocorrelations were displayed graphically, plotting lags against autocorrelation or partial autocorrelation factors.

Information from these autocorrelation techniques was used to narrow the scope of analysis of potential lag variables. The most likely candidate lags were selected, and then analyzed using the step-by-step regression procedure recommended by Enders (2010). First a stepwise linear regression is used to evaluate the potential lags and to refine a multivariate lag model. Enders (2010) recommends starting with a relatively long lag length and then paring down the model using t- or F-tests. Regression diagnostics were run to ensure that there was no structural change or serial correlations in the residuals, which should appear to be white noise in a correlogram. To determine the ideal bivariate lag, reduced nested models are tested using the Akaike Information Criterion (AIC). Lower values for the AIC represent a model which contains more information, and information loss percentages can be calculated with simple arithmetic. Regression, regression diagnostics, and model specification were performed in STATA.

5.2 Empirical Dynamical Modeling

In the previous chapter and in first section of this chapter the discussion has revolved around time series. However, recalling Chapters 1 and 2, we must now refocus our discussion away from a set of time series and onto an attractor manifold in multidimensional state space. Critically important here is the idea that parametric equations may not be necessary to describe the behavior of a dynamic system. In Sections 2.1.3 and 2.1.5, I discuss how the behavior of a certain class of coupled nonlinear systems can be hypothesized to manifest itself in certain geometrical forms in multidimensional state space. I elaborate that discussion here starting not from the parametric alternative, but from the existence of that attractor manifold.

For non-chaotic systems that can be described as a point in high-dimensional space, EDM provides information on appropriate embedding dimensions through simplex projection, insights on nonlinearity in the system though S-mapping, and analysis of causal relationships between variables through CCM. EDM is rooted in Generalized Takens' Theorem, which states that an attractor manifold can be reconstructed from lags of different time series so long as those time series are part of the same system (Takens, 1963). A way to think about this is that if entries are linked to exits then their relationship should be predictable in some way as those variables move through time. And even if we do not know the rate and capacity parameters which may govern those movements we can observe the linked movements. The key features that allow for the application of EDM are a coupled causal relationship over time of two variables, the assumption is that as these variables move together that joined nature of their relationship—the coupling—will produce a geometric shape in multidimensional space, the existence of which can be inferred by the coupled behavior of the variables over time.

The benefits of nonparametric causal analysis are clear, especially for systems where there is little information about the dynamics. Over the last four years, EDM has found applications in diverse fields. Growing out of theoretical ecology, there are numerous applications within the biological sciences (Deyle, et al., 2016; Ye, et al., 2015). EDM and CCM have been used to model climate and environmental factors, including air pollution (Yao, 2017; Kirk, et al., 2016). In the social sciences, CCM has been used to detect the impact of marketing over time (Dost & Maier, 2017; Dost, 2015; Huffaker & Fearne, 2014), the interconnection of behaviors on social media (Luo, et al., 2014), and in examining causal drivers of price volatility in market systems (Huffaker, et al., in press 2017). CCM has found applications in medicine and neuroscience (Verma, et al., 2016; Wismuller, et al., 2016; Schiecke, et al., 2015). Closer to the out-of-home care context, EDM has been used to examine developmental outcomes in language across time (Irvin, et al., 2016). There have also been some exploratory studies using EDM in congregate care systems (Wulczyn & Halloran, 2017a; Wulczyn & Halloran, 2017b). Recent advances in this kind of nonparametric modeling have focused researchers on how to derive equations from the EDM analysis (Rudy, 2017; Brunton, et al., 2015; Ye, et al., 2015). This area of research is developing and beyond the scope of this dissertation.

The causal claims available in EDM, in CCM in particular, are not without criticism (Cobey & Baskerville, 2016; but see Sugihara, et al., 2017). Those criticisms revolve around distinguishing between covariates and causal drivers, including synchrony and seasonality. Cobey & Baskerville's (2016) critique of EDM was undertaken using a well explored coupled time series with known behavior and parameters, and they found EDM to fail in some causal predictions linked to that series. While those criticisms are well taken, and should be cause for caution in the application of this method, I would like to note two things: First, this is one of the first studies to explore dynamic behavior of child welfare time series, and little theory and empirical evidence supports priors in the analysis of these time series. Second, this study overtly acknowledges that "causal" linkages here are not necessarily driven by the variables in the study, with, instead, the variables here being used as proxies for resource constraints which may not be observable in practice-relevant time frames.

This section proceeds as follows: First, I describe simplex projection as a method of separating noise from nonlinear patterning. Second, I discuss s-mapping, which focuses on predictable univariate behavior in nonlinear space, and can be used to tune the dimensionality of analysis. Third, I lay out several other methods of analyzing embedding dimensions. Fourth, I describe the CCM method.

5.2.1 The Complexity of a System: Simplex Projection

A first stem in modeling a dynamic system is determining the complexity of the system. In EDM, we use simplex projection (Sugihara & May, 1990) to determine whether variation in a univariate time series is random or whether patterns of relationships can be determined in higher dimensions as relevant near-neighbor points emerge in patterns as the time series is folded in phase space. This provides two pieces of information: firstly, simplex projection provides information about the predictability of the attractor manifold (can we infer the existence of coupled entry and exit behavior using this method); secondly, it provides an estimate of the embedding dimension which provides the most predictable attractor behavior (how do we calibrate the method to see relationships that exist outside of two dimensions). In the first case, simplex projection reports values of rho—zero representing a completely random system (no predictive relationship between entries and exits), and a one representing a completely deterministic system (one where a change in the number of entries causes a defined change in the number of exits) describe the predictability of the attractor in the system. In the second case, a series of rhos are reported across different embedding dimensions, again the embedding dimension at which the highest value of rho is found is the embedding dimension where the attractor is the most predictable. Embedding dimensions can be conceptualized as the minimum number of points in state space required to define the attractor—thus, an embedding dimension of zero represents a linear system, and an increasing embedding dimension represents more highly folded state space. Think, for example, about the number of dimensions required to differentiate a cylinder, a sphere, and a circle: In two dimensions (and from certain angles) a cylinder, sphere, and circle may not be differentiable. However, in three dimensions we are able to see the difference in the three shapes. Similarly, relationships between entries and exits may not be identifiable in two dimensions, but become clear in higher dimensions. The simplex projection calculation is contained within the R package {rEDM}.

5.2.2 Embedding Dimension: Alternative Methods

An alternative method to determine embedding dimension is False Nearest Strands (FNS) estimate proper embedding dimensions for single-variable time series. False nearest strands make use of the trajectory of points across attractor space in different embedding dimensions. The predictability of these strands at a given embedding dimension allows for the assessment of the fit of that embedding dimension. These are reported as percentages of FNS, and the optimal embedding dimension is selected by looking at the lowest percentage value occurring at the lowest embedding dimension. Some discretion is required here in order to balance the percentage values of FNS against the information loss and complexity required for higher embedding dimensions. The calculation was done in the R package {fractal}.

5.2.3 Embedding Dimension: S-mapping

After an appropriate embedding dimension is selected, we can next gain some insight into whether the hypothesized attractor displays predictable nonlinear behavior. The importance of this test is distinguishing spurious correlations from signals within the data. Thus, S-mapping can be used to examine deterministic coupling in time series (Sugihara, 1994). S-mapping predicts nonlinearity where values of a weighted tuning parameter, theta, in nonlinear space exceed those values in linear space. Specifically, theta amplifies the difference between observed distance and average distance between nearest neighbors. In a linear system, then, a theta of zero gives the best predictions. In a nonlinear system, however, increasing the weight (driven by an increase of theta) increases the locality of the prediction in phase space, indicating that nearer neighbors are more predictive than global average distances. Thus, a S-map indicates nonlinear dynamics in a time series for a given embedding dimension determined by simplex projection. In nonlinear systems the relationship between the value of x and the value of y cannot be described in a model based on direct proportions. Because x and y are not linearly correlated in a nonlinear system linear autoregressive models of the system may not be able to describe the system significantly better than the mean value of the series. Thus if there is nonlinearity within a time series other methods should be considered. S-mapping is done in the R package {rEDM}.

5.2.4 Convergent Cross Mapping

Convergent cross mapping (CCM) provides a statistic for the predictability of the orbit of an attractor manifold in a two-variable system. CCM provides our first opportunity to test whether exogenous variables lie within a single attractor manifold—for example, whether out-of-home care entries and out-of-home care exits are coupled or whether out-of-home care entries are linked to dependency court subsystem case openings. This procedure provides two valuable insights. First, whether two variables lie on the same attractor manifold. Second, whether the relationship between the two variables is predictable and causal. Sugihara, et al. (2012) describe CCM as a method to detect casual relationships between weakly coupled variables in dynamic ecological populations. CCM predicts whether variables share a causal relationship governed by an attractor manifold by cross-predicting variables that are observed from the same dynamic system (Ye, et al., 2015). CCM, then, provides a quantifiable analytic window into whether a predictable nonlinear attractor manifold exists within that system.

Tuning the system according to the time lag and embedding dimension determined above, CCM tests for the degree to which entries are functionally coupled with lagged entries. CCM does this by tracing the lagged variables within a given embedding dimension. The insight is in the number of coupled pairs included—from a relatively small series (randomly drawn from the whole length of the series), to a series that is close to the length of the observations. This process is repeated over a series of bootstraps. Because causal attractor behavior should be increasingly predictable as a series of lagged variables, called a library, is increased, then we can infer, if there is a convergence from small library sizes to large library sizes, that the linkages between the variables are causal.

CCM was performed using the R package {rEDM}. CCM makes use of the lag lengths determined above, as well as the embedding dimension determined by Simplex Projection and False Nearest Strands. Because CCM is predicated on assessing the correlation between libraries of varying lengths, analysis here is done using a maximum of 770 library pairs—just shorter than the length of the time series. The library counting procedure in CCM starts with 10 pairs and then counts by tens up to 770 pairs. The CCM procedure is bootstrapped ten times for each library length. The reported rho function is the mean rho of the bootstrapped samples at the largest library length.

The rho function ranges in value from zero to one, with zero being a random system and one being a fully deterministic system. The literature applying CCM remains in its infancy, but provides some insight into meaningful values for CCM coefficients. In natural systems, discussions about meaningful effect sizes start at CCM coefficients of around 0.1, and the reported range of analysis goes from coefficients of less than .03 to approximately 0.85 (Evans, et al., 2016; Clark, et al., 2015; Tsonis, et al., 2015; and Sugihara, et al., 2012). In addition to the raw value of the coefficient, comparisons of the CCM coefficient and the correlation coefficient were also used (Tsonis, et al., 2015).

To determine whether the CCM results can be differentiated from random, and, additionally, whether the behavior of the system is the result of coupled behavior or the synchronous nature of the time series, an ad-hoc hypothesis test was performed. Statistical significance was determined by randomly shuffling observed time series data, that is, completely reordering the observed values of the time series randomly. These random distributions are analyzed using the CCM method described above, and then compared to the observed distributions to see the percentage of matched library pairs where the rho of the random data set exceeds the rho of the observed data set. This value approximates a p-value.

Chapter 6
Quantitative Analysis: Results

The descriptive data analysis done in Chapter 4 suggests that the child welfare time series that are the subject of this dissertation have weak systematic patterning on the linear scale. All time series contained information at higher dimensions. Nonlinear dynamical analysis found nonlinearities present within most studied time series. Coupling was observed in some time series both in univariate and bivariate systems, though the evidence for predictable patterned dynamic coupling was strongest within univariate systems and within out-of-home care or dependency court subsystems. Findings in out-of-home care in three counties indicate that exits are a stronger driver of entries than entries are of exits, though entries-driving-exits was found to be a significant dynamic in two study counties. Other than coupling between out-of-home care entries and court case filings, coupling between out-of-home care and dependency court systems was weak or nonexistent.

6.1 Lag Determination

As noted in Chapter 5, time series analysis, and in particular nonlinear analysis, is highly sensitive to time lags and there is little theoretical and empirical basis with which to guide lag selection. Several a priori approaches were attempted: Computational and graphical autocorrelation methods, and general-to-specific multivariate regression models. Results indicated no systematic patterning in lag lengths across variables either among or between the sample counties. Lag lengths ranged from one- to eight-weeks. Table 6.1 summarizes the lag determinations.

Table 6.1: Best Lag Lengths as Determined by Autocorrelation and Regression Analysis by County

Variable	Clark	King	Pierce	Spokane	Snohomish	Yakima
FE	7	1	1	8	7	6
FR	8	1	4	4	1	1
CF	6	6	1	2	7	4
CD	8	1	4	5	2	5
Fdelta	6	1	2	8	1	6
Fvol	1	1	1	6	6	1
Cdelta	6	3	2	3	6	7
Cvol	6	6	4	5	7	7

For thirty-nine of the forty-eight variables, simple autocorrelative relationships predicted the same lag as was selected by regression analysis. In cases where that was not true, it was typically because there were two or more lag values which were approximately the same. For example, for out-of-home care exits (FE) in Clark County, correlation coefficients for lags one (0.1898), six (0.1733), and eight (0.1778) were very close in value. Comparing the explanatory value of each of those lag lengths in a regression model gave lag eight as the most explanatory using the AIC.

The intra-variable lag correlation coefficients for the best lag lengths ranged from weakest, a negative correlation of 0.0090 (Fdelta in Spokane County), to strongest, a positive correlation of 0.3476 (Cvol in Spokane County). Most linear correlation coefficients fell within the 0.10 to 0.20 range, indicating faint positive relationships between a variable and its past states. Systematically, the strongest relationships were between the aggregated volume variables (Cvol and Fvol): giving relationships of 0.3476 (Cvol, Spokane), 0.3237 (Cvol, Pierce), 0.2544

(Fvol, Yakima), 0.2531 (Fvol, Clark), 0.2518 (Fvol, King), and 0.2076 (Fvol Pierce). Across counties, the weakest relationships were between the delta terms: 0.0986 (Cdelta, Clark), 0.0734 (Fdelta, Pierce), 0.0733 (Fdelta, Clark), 0.0596 (Fdelta, Yakima), -0.0462 (Cdelta, Yakima), and -0.0090 (Fdelta, Spokane). Similarly, the amount of variance explained in a bivariate regression between a variable and its lagged predictor were very small—ranging from less than one percent (FE, Snohomish) to just above twelve percent (Cvol, Spokane) with the mean explanation of the variance at roughly three percent.

6.2 Empirical Dynamical Modeling

The results from EDM of the out-of-home care and dependency court systems are presented here. In the first part, I discuss the determination of the complexity of the system, including a discussion about the within-variable predictable nonrandomness. Secondly, I discuss nonlinearity in these time series. Finally, I discuss the bivariate coupling of variables within and among out-of-home care and dependency court.

Table 6.2: Simplex Coefficients for Clark County

Variable	Simplex Rho
FC entry	0.1244
FC exit	0.1654
Court entry	0.1216
Court exit	0.0952
Fdelta	0
Fvol	0.2772
Cdelta	0
Cvol	0.1134

6.2.1 The Complexity of a System: Simplex Projection

There are two findings to be discussed in this part. First, I will discuss the results related to the predictable coupling in lagged single-variable systems. Second, I will discuss the dimensional tuning parameters which will be applied to later analysis.

6.2.1.1 Coupling in Lagged Single-Variable Systems

Simplex projection found that thirty-seven of the forty-eight variables displayed some degree of predictable coupled patterning between a variable and its lagged states. Table 6.2

presents the simplex coefficients for Clark County. The way to read Table 6.2 is that the variable, for example, out-of-home care entries (FC entries), is coupled with itself across the determined lag length. So the question is to what degree out-of-home care entries from seven weeks ago are predictive of the present number of out-of-home care entries. Table 6.2 indicates that the simplex coefficient for that relationship is 0.1244. Using the out-of-home care entries as an example, analysis found that the number present entries and the number of entries from seven weeks ago were linked in a loosely coupled way. That is, they indeed move together, but not deterministically.

Table 6.3: False Nearest Strands Embedding

Clark County Court Filings

E	FNS%
1	44.33
2	46.47
3	43.65
4	43.90
5	44.25
6	44.70
7	45.30
8	48.85
9	47.33
10	47.35

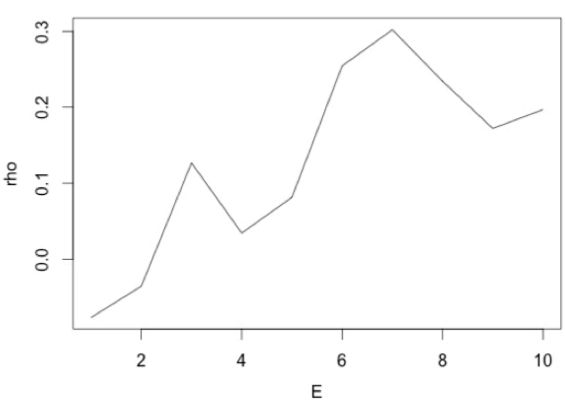
Interpretation of these coefficients are domain-specific, and there is little insight from the social world as to the precise meaning of a particular coefficient value. For the purposes of addressing the hypotheses presented in this dissertation, I am defining any nonzero coefficient as presenting some evidence of nonrandomness in the child welfare time series. The results from Clark County are typical in that the lagged delta terms for both the out-of-home care and court systems were found to not be predictive of future system states. In fact, seven of the eleven variables which did not display coupling were measures of delta variables (the other three were court case openings in Snohomish and Yakima Counties, out-of-home care entries in Snohomish and Spokane Counties). Similar to the lag identification process, there is little systematic patterning in the distribution of the strength of these simplex coefficients across variables or within counties—other than the delta variables and the fact that Snohomish County has an overall lower effect size than the other study counties. Generally speaking, the intra-variable relationships were stronger in the out-of-home care system when compared to the dependency court system.

Simplex coefficients for all of the study counties are reported in Appendix C.[1]

6.2.1.2 Embedding Dimension

All time series within the study displayed dimensional complexity. Considering the circle/sphere/cylinder example from earlier, what this means, for example, is that the child welfare data analyzed here has more information about the relationship between entries and exits in higher dimensions than it does in strictly linear terms. In other words, analyzing this data set linearly we may not be able to differentiate between a sphere and cylinder. Higher embedding dimensions were present in all study variables. Dimensionality was constrained in the one to ten range, the dimensionality of the time series was not generally systematic either by county or by variable. Moreover, competing methods of selecting embedding dimensions similarly varied widely across time series. In general, False Nearest Strands methodology skewed toward lower embedding dimensions than did simplex methods. Consider, as an example the embedding dimensionality of maltreatment court case filings in Clark County. Table 6.3 reports the percentage of false nearest strands across a number of embedding dimensions for that system—recall that we are seeking to minimize

Figure 6.1—Simplex Values by Embedding Dimension for Clark County Court Case Filings



This figure presents a simplex plot of rho coefficients (y-axis) across different embedding dimensions (x-axis).

[1] A note about statistical significance: All simplex and CCM coefficients reported in this dissertation are statistically significantly different than zero ($P \leq 0.05$) unless otherwise indicated. In the appendices, coefficients which do not meet that level of statistical significance are indicated in all non-zero values with italics and a lightly greyed cell.

the number of false nearest strands in selecting the appropriate embedding dimension in this method. Contrast that table with the simplex projection plot in Figure 6.1—in simplex projection the best embedding dimension is where the rho is maximized. In this example, the nadir value for the false nearest strands method is at an embedding dimension of three. In the simplex projection, though there is a peak embedding dimension value at three, but the maximum does not occur until an embedding dimension of seven. In this case an embedding dimension of three selected as appropriate because of the combination of the nadir value in false nearest strands and the slight peak in the simplex projection. Additionally, the false nearest strands percentages reported for the court filings time series are typical of values found for all the variables in the study, where most percentages for false strands were in the forties with a range from the low thirties to the high fifties. Embedding dimensions for variables all study counties are in Table 6.4.

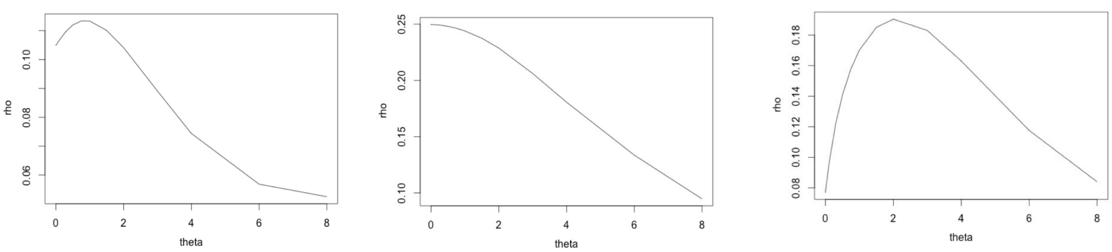
Table 6.4: Best Embedding Dimensions by County

Variable	Clark	King	Pierce	Spokane	Snohomish	Yakima
FE	3	9	6	6	6	8
FR	3	4	7	5	5	5
CF	3	9	7	5	4	6
CD	4	6	6	5	5	6
Fdelta	9	5	9	3	3	8
Fvol	5	3	10	4	3	6
Cdelta	5	3	5	10	10	10
Cvol	3	4	4	3	6	4

6.2.2 State-Dependent Nonlinearity in Time Series

All time series in this study displayed some degree of nonlinearity. Thus, instead of entries changing at some proportion of exits, there is a linked but nonproportional relationship between entries and exits. More than half of the series analyzed (28 out of 48) displayed a degree of state-dependent nonlinearity such that appropriate analysis requires nonlinear methods. Figure 6.2 presents three example plots from the s-mapping procedure drawn from the Clark County out-of-home care and court time series. All three of these plots indicate some nonlinearity in

Figure 6.2—Measures of Nonlinearity in Clark County Out-of-Home Care and Court Time Series



(a) (b) (c)

This figure presents in the s-map measures of nonlinearity in three Clark County time series. The y-axis is rho, a coefficient measure of prediction ability with one being the maximum and zero being the minimum. The x-axis is theta—a nonlinear tuning parameter—where the value of zero represents a linear system and increasing values indicate nonlinearities. (a) Out-of-home care entries. (b) Out-of-home care exits. (c) Dependency court exits.

child welfare time series through nonzero values of rho along thetas representing nonlinear tuning. Even in the second plot—marked (b), and representing out-of-home care exits—where the maximum theta value of zero indicates that linear systems can be adequately used to describe the system, there are still nonzero rho values across multiple nonzero values of theta. Even though the out-of-home exits displayed nonlinearities, that time series is not defined as a state-dependent nonlinear time series because of the adequacy of the linear prediction—or, more specifically the difference between the rho value at a theta of zero and the value of the maximum rho value at a nonzero theta is negative. This distinction has methodological consequences: if a time series is state-dependent nonlinear then nonlinear analysis techniques are required, whereas linear and nonlinear methods can be applied to series with nonlinear and linear components. This technical difference—time series which displayed nonlinearities but did not meet the definition of state-dependent nonlinear time series—applied to twenty studied variables.[2]

6.2.3 Convergent Cross Mapping

The results from the convergent cross mapping analysis were mixed. Related to Hypothesis 1, Part 6.2.3.1 describes within system analysis which found some relationships between variables existing in either the dependency court or out-of-home care systems, which generally reinforces the findings from simplex projection. On the other hand, related to Hypothesis 2, Part 6.2.3.2 describes what, on the whole, are weak inter-system relationships between dependency court and out-of-home care systems—especially considering the main variables of interest in this study (out-of-home care entries and exits; dependency court case openings and closings). Findings for the constructed variables representing change in population and system volume showed stronger results for inter-system relationships.

6.2.3.1 CCM Within Out-of-Home Care or Maltreatment Court Systems

For the main variables in this study, CCM found predictable coupling within the out-of-home care subsystem, but not within the dependency court subsystem. That is that entries and exits in the out-of-home care subsystem were related across time in a way that case openings and closings in the dependency court subsystem were not. No coefficients in the openings-predict-closings or closings-predict-openings couplings were found to be statistically different than zero, indicating no evidence of predictable nonrandom coupled pattering between those variables

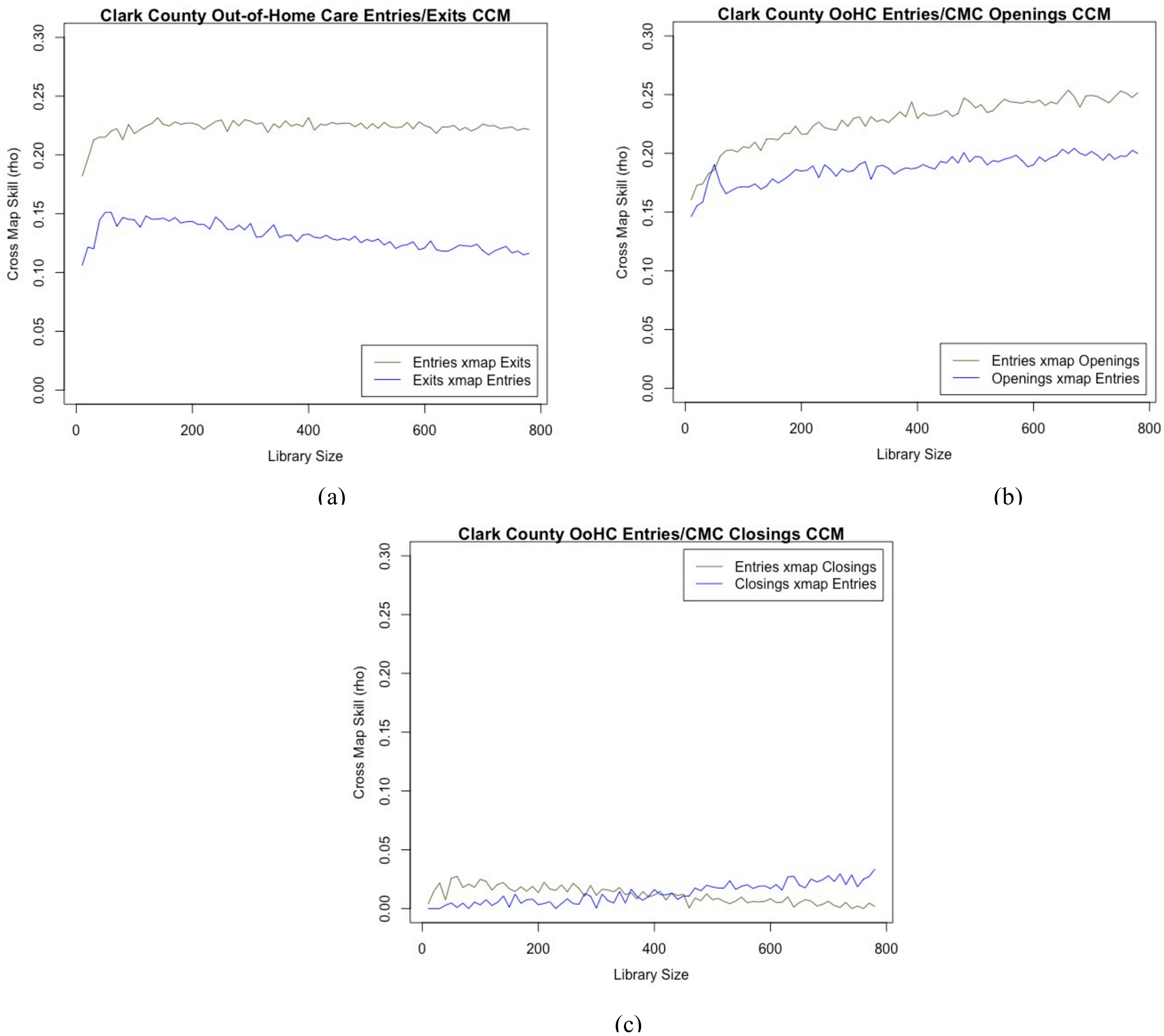
[2] Those variables included: Out-of-home care entries (Clark, Pierce, Yakima), exits (Snohomish, Spokane, Yakima), delta (King, Pierce), and volume (Clark, King, Spokane, Yakima). Court openings (Clark, Spokane, Yakima), closings (Spokane), delta (King, Pierce), and volume (King, Pierce, Yakima).

under these study conditions. In four of the six study counties, analysis found coupled linkages between out-of-home care entries and out-of-home care exits. In three of these counties the effect size was slightly larger for the exits-predict-entries direction as opposed to the entries-predict-exits direction. For example, in Clark County, the coefficient for exits-predict-entries was 0.2318, whereas the coefficient for entries-predict-exits was 0.1512. This difference indicates that exits are a stronger driver of entries than entries are a driver of exits. Or in other words, that exits were a better predictor of entries than entries were of exits. Additionally, it should be noted that the CCM exits-predicts-entries coefficient, 0.2318, is a substantial improvement over the correlations coefficient for the same relationship at the same lag, 0.0937. This difference in predictive skill is related to the additional information which lies in the nonlinear manifold as compared to the linear relationship between the two variables.[3] The Clark County case provided the largest difference in effect size.[4]

Figure 6.3(a) presents the CCM results for the coupling of Clark County out-of-home care entries and exits. There are several features of this Figure which require explanation. First, note that the exits-predict-entries coupling is represented by the green line and the entries-predict-exits coupling is represented by the blue line. The x-axis represents the library size across which the convergent cross map is drawn.[5] The y-axis represents the CCM coefficient. One notable feature is the curvilinear improvement in forecast skill for the exits-predict-entries coupling before, at just under a library size of 200, the CCM coefficient values level off. This shape is indicative of two related variables. By placing both of these plots on one graph, we are

[3] A correlation matrix is provided as Appendix D, listing the correlation between study variables at appropriate lag lengths.
[4] Entries-predict-exits compared to exits predict entry values for other counties were 0.1037/0.1661 (King); 0.0775/null (Pierce); 0.0308/0.0041 (Snohomish—neither value statistically different than zero); null/0.0136 (Spokane—exits-predict-entries not statistically different than zero); and 0.1667/0.1642 (Yakima).
[5] Recall from Chapter 5.2.4 that CCM employs an increasing number of randomly drawn coupled pairs in order to test for forecast improvement.

Figure 6.3—Convergent Cross Maps for Out-of-Home Care and Dependency Court Systems



This figure presents convergent cross maps for three different paired variables. (a) Out-of-home care entries and exits. (b) Out-of-home care entries and dependency court openings. (c) Out-of-home care entries and dependency court exits (a finding not differentiable from zero).

able to evaluate the directionality, if any, of the relationship between the two variables. Even though there is some predictive coupling in the entries-predict-exits series, it is relatively weaker when compared to the prediction operating in the other direction.

Interestingly, the constructed variables of weekly difference and total system volume displayed stronger intra-system coupling. That is to say that the volume-delta relationship within both out-of-home care and court systems were predictive across lags in eleven of the sixteen subsystems. Moreover, the delta and volume variable were also coupled with the entries/openings and exits/closing variables. This relationship was present bidirectionally in each subsystem in each county. The coefficients for the relationship between the delta and volume variables and the entries/openings and exits/closings variables were substantially higher, in general, than those for the entries-exits or openings-closings couplings.

6.2.3.2 CCM Between Out-of-Home Care and Dependency Court

As a threshold matter, as discussed in Chapter 4, the policy and practice structure of the Washington State child welfare system would predict some degree of coupling between out-of-home care entry events and dependency court case openings.[6] Therefore, the strongest chance of seeing inter-system relationships between dependency court and out-of-home care systems would be in the coupling of those two variables. That relationship was detected in all six counties in the present study. The strength of those results, however, were not indicative of the strength of other inter-systemic relationships.

There were two other systematically notable relationships. First, there is a relationship between out-of-home care exits and court case closings, the strength of which varies across the sample counties, but which is present in five of the six studied counties (the exception being Clark County where that relationship was not statistically different than zero). In five of six counties, there is a bidirectional or unidirectional coupling between out-of-home care exits and dependency court case closings. In King and Spokane counties, there is a very weak unidirectional coupling for closings-predict-exits (coefficients of 0.0607 and 0.0696 respectively). In Piece, Snohomish, and Yakima, these two variables displayed bidirectional

[6] For reasons more completely described in Chapter 4, with limitations that are also described in that chapter.

coupling with coefficients for closings-predict-exits of 0.2011 (Pierce), 0.0510 (Snohomish), and 0.0548 (Yakima); and for exits-predict-closings of 0.1772 (Pierce), 0.1077 (Snohomish), and 0.0775 (Yakima). Secondly, the delta term (entries minus exits or openings minus closings) is coupled between the two systems in each of the counties studied. In all six counties there was a bidirectional relationship between the court delta term and the out-of-home care delta term.

Returning to Figure 6.3, (b) and (c) display results from inter-system analysis. The first, (b) presents a coupled result from out-of-home care entries and dependency court case openings. In Figure 6.3(b) we can see the predicted relationship between those two variables as bidirectional coupling. For both entries-predict-case openings and case openings-predict-entries, there is an average increase in prediction skill across library length—though openings are competitively more predictive of entries, than entries are of openings, it is a small overall difference. On the other hand, Figure 6.3(c) presents a null result. It describes the coupling of out-of-home care entries and dependency court case closings. Neither direction suggests a relationship that has an effect size statistically different from zero.

CCM coefficients for all of the study counties are reported in Appendix E.

6.3 Summary of Quantitative Analysis

The method used to described the lag lengths was selected to identify systematic patterning within the individual time series. The patterning that was found using this method varied in strength (from correlation coefficients of practically zero to .3476) and lag length ranging across variables and within counties (see Table 6.1). The variability of the lag lengths has both practical and methodological implications. These are discussed at length in Section 7.1.1.

This study found nonrandomness and dimensional complexity in many of the time series. Recalling Section 2.1.4, randomness for the purpose of this study is defined as the unpredictability of the coupling between a variable and the lagged state of that variable or another variable. In just more than three quarters of time series simplex projection found nonrandomness. Not only did this study identify nonrandomness in child welfare time series, but it identified dimensional complexity in all time series. Higher dimensional geometric structures in child welfare time series mean that there is information about the relationship between a variable and its lagged state outside of linear or two-dimensional analysis.

System effects were studied in two ways in this dissertation. First, related to Hypothesis 1, the relationship between variables within the out-of-home care or dependency court subsystems. In the out-of-home care subsystem, predictable coupling was identified in the main variables. That means, for example, that coupling was identified between out-of-home care entries and lagged out-of-home care exits. In many cases, as described above, these nonlinear relationships were improvements over the linear relationships of the same two variables. The strongest evidence of this nonrandomness was in the moderate relationship between week-to-week entry/exit dynamics and net population change. Similarly, moderate relationships were found between week-to-week entry/exit dynamics and total weekly entries plus exits, and between net and total series. There is weak, but extant, coupling in entry/exit dynamics in two thirds of the tested systems. Second, and related to Hypothesis 2, the relationship between variables between out-of-home care and dependency court. Because of the legal and practice interrelationship between the act of out-of-home placement and the opening of dependency court proceedings, I expected to find relationships between variables in these two systems. This relationship was identified in analysis. Though several other coupled relationships were identified between the out-of-home care and dependency court subsystems, the overall evidence of an interrelationship between these subsystems across other variables was weak and only present in half of the counties studied.

Chapter 7
Discussion and Conclusion

The purpose this study was to apply systems thinking to child welfare by situating the determinants and structures of population as an empirical object of study. This dissertation focused on a population theoretical perspective that identifies entries, exits, capacity, and feedback as primary drivers of population phenomena (see Wulczyn, 1996). The investigation was shaped by the threshold empirical question of whether there is sufficient evidence of predictable population-level coupling in child welfare time series to justify the application of population theory in child welfare research, policy, and practice. The answer to that question is a qualified yes: child welfare time series analysis provides some support for modelling child welfare populations as coupled feedback systems.

This chapter begins with a discussion about the results laid out in Chapter 6, focusing on time lags, nonlinearity, patterning in single-variable systems, and patterning in bivariate systems. The chapter continues by applying the mixed evidence to the hypotheses outlined in Chapter 2. Next, I discuss limitations of the present study: primarily as they relate to specifying the most meaningful constructs, and methodological limitations in lag determination. Finally, this chapter concludes with a discussion of the implications of this study for future research and for child welfare policy and practice.

7.1 Discussion

Returning our focus to the conceptual model presented in Chapter 2:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = r'\pi'x(t) - r'y(t)$$

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = r''\pi''y(t) - r''x(t)$$

which represents a way of thinking about child welfare populations where entry/exit dynamics are impelled by criterion capacity values and managed by feedback looks across time. With that conceptual model again in mind, this section discusses and analyzes the major findings of this dissertation and the degree to which they support or do not support the application of that theoretical model.

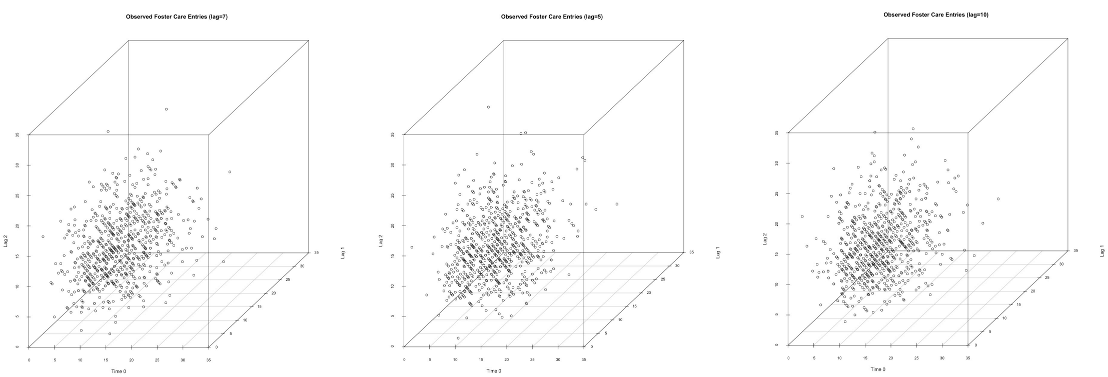
7.1.1 Time Lags in Child Welfare Time Series

It is useful at this point to consider the theoretical importance of time lags in dynamic modelling. The time lag is the system response time—the temporal distance between when information is absorbed into the system and when a system's response to that information is manifested. Prior literature and theory provides no estimate for what a such a value might look like in a fine-grained temporal frame for child welfare practice. This gap in knowledge was remedied, in part, through the qualitative study which provided a broad frame in which to understand the responsiveness of the child welfare system—specifically one week to approximately three months. In addition, the method employed by this study—identifying lag values as a threshold matter within a single variable—was an attempt to determine lag-based patterning in a systematic way, and to avoid tuning the lags in a post hoc fashion to maximize coefficients.

I found a high degree of variability in lag length times both within a given county, and for a given variable across different counties. This degree of variability was likely predicted by theory—that is by different feedback structures acting to govern different systems in different structured ways. However, the existence and degree of variability presents a challenge in analyzing lags among and between systems and creates a ripple effect for further analysis. The coupling that existed among the variables was also very linearly weak. Given the descriptive statistics for these variables presented in Chapter 4, the weakness of these relationships is unsurprising. I would like to begin this part by thinking about what we have captured in the lag determination. I will then continue by describing a post hoc analysis that was used as an alternative to the approach described in Chapter 5.

Figure 7.1 presents a lag plot for three different lag values for out-of-home care entries in Clark County. These entries have a linear correlation coefficient for the selected lagged (τ=7) coupling of 0.1538, and regression analysis gave a significant coefficient and an R^2 value of 0.0237. Out-of-home care entries in Clark County were selected for this example because they

Figure 7.1—Lag Plots for Three Different Values of Tau in Out-of-Home Entries (Clark County)



(a) (b) (c)

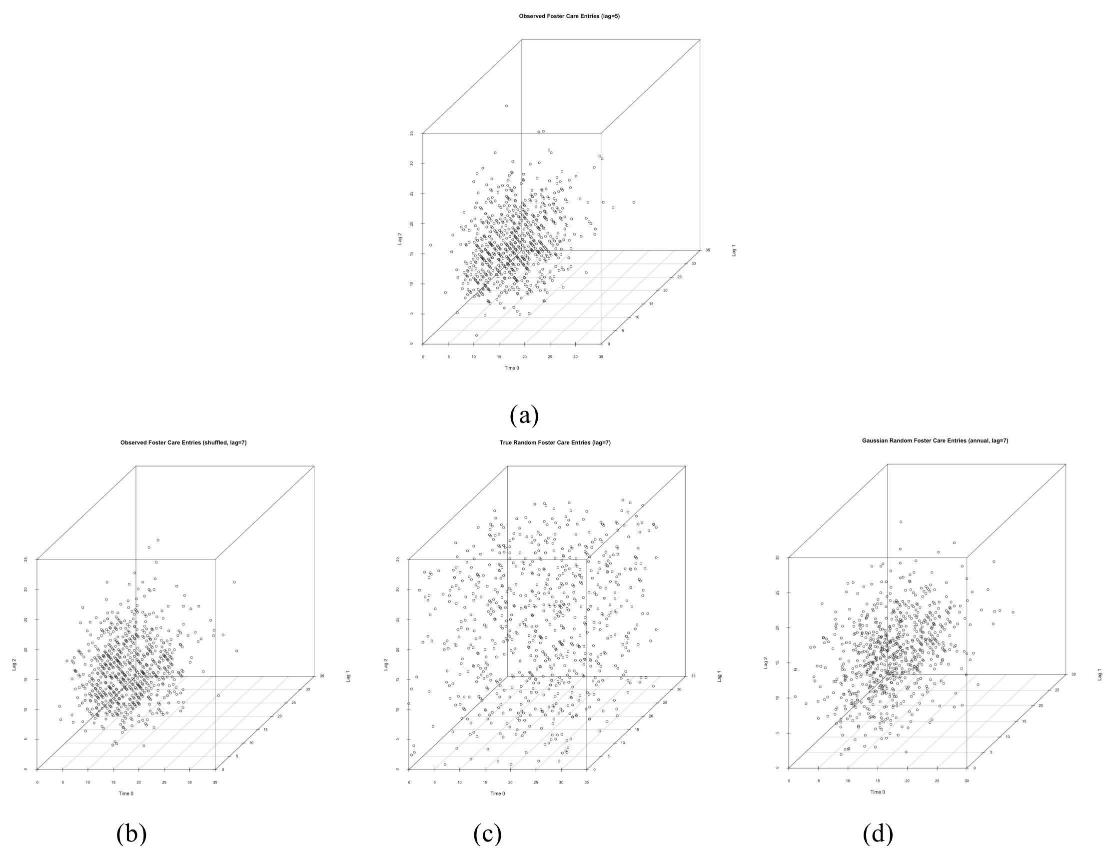
This figure presents lag plots at three different values of tau for the out-of-home care entry system in Clark County. (a) represents the lag (τ=7) identified as the best fit; (b) represents τ=5; and (c) represents τ=10.

present a general example of the problem of empirical lag selection.[1] The lag plots are created by setting the *x*-axis at time zero, then the *z*-axis at the first lag, and the *y*-axis as the second lag. This method presents a portrait of a point as it exists in three-dimensional space held by its most proximate lags. These plots are visual diagnostic tools which allow you to see the grouping of lagged points in time. In Figure 7.1, the selected lag (τ=7) represented in (a) does show a

[1] It is hard to generalize because of the variability in correlation among the variables and counties. Some selected lag lengths are almost indistinguishable from random in the plots (e.g., out-of-home care entries in Snohomish County, and court case closings in King County), whereas others present much more distinguishable patterning (e.g., court case filings in Pierce County, and out-of-home care entries in Yakima County). The Clark County case presents a middle-of-the-road example.

patterned grouping within the three-dimensional field, but it is difficult to determine any distinction between it and nearby lags. In fact, the shorter lag length (τ=5) represented in (b), appears to have a more compact form. Figure 7.2 presents the same kind of plot, except that it compares the observed data to three types of randomly generated data—randomly shuffled data, complete random generated data (based on the mean and standard deviation of the observed time series), and annually randomized data based on the Gaussian distribution of the individual annual increments of the time series. Unlike Figure 7.1, Figure 7.2 reveals clear

Figure 7.2—Lag Plots for Observed and Random Data in Clark County Out-of-Home Care Entries



This figure presents in (a) the observed out-of-home care system in Clark County at τ=7. The three lower plots each represent different kinds of randomly generated data also presented at τ=7. (b) is the observed data for the out-of-home care system in Clark County randomly shuffled. (c) is a complete random production of points based on the mean and standard deviation of the observed time series. (d) is randomly generated points based on a Gaussian distribution which breaks the fifteen-year time series into annual portions, generates random data based on the mean and standard deviation for that year.

distinctions between the four plots—importantly with the observed data being clearly differentiated from the totally random and annualized Gaussian plots. While the observed data (a) does appear most similar to the shuffled observed time series (b), the clustering of the observed data is less spherical and more linear. But the similarities between the plot for the selected lag to alternative lag choices in Figure 7.1 and the shuffled time series in Figure 7.2 do bring up questions about the a priori lag selection protocol selected for this study, and the utility of the lags that were selected using that method.

It is worthwhile to pause here, momentarily, to recall that the results for EDM reported in Chapter 6 and described in the next parts of this chapter *do* indicate relationships between and among many variables in this study. So, viewing the question of the lag tuning at its most optimistic: the nonlinear dynamical relationships in this study were strong enough to be detectable under less than ideal conditions of linear lag selection. The importance of lags to the underlying conceptual model in this dissertation, however, demands a high level of scrutiny of these results. Further limitations of this study due to the lag selection protocol are discussed in Section 7.3, *infra*. Directions for future research related to lags in child welfare time series are discussed in Part 7.4.1, *infra*.

Table 7.1: Out-of-Home Care Entries (Clark County)—Lag Lengths and Simplex Coefficients

Lag	Simplex	Autocorrelation
1	0.1592	0.1137
2	0.1729	0.1143
3	0.2294	0.1276
4	0.1517	0.1328
5	0.1553	0.0958
6	0.2073	0.1452
7	0.1244	0.1538
8	0.1315	0.1250
9	0.1626	0.0954
10	0.1057	0.0779

For our purposes here, two possible explanations need to be explored further. First, it is possible that a linear method of determining lag lengths is inappropriate for systems that exhibit the nonlinearity identified in these time series. Moreover, though the approach of attempting to identify patterned lag structure within a single variable may have been misguided. It is possible that the bivariate lag structure is resonant at a lag length that is independent of the "best" lag for either of the univariate time series. This is theoretically sensible since the feedback structure which couples two variables may be unique from the feedback structure which governs a single variable. If this is the case, it may be possible to simply select a bivariate lag using correlations between bivariate time series and select a maximized coefficient over a certain time span. It is important to identify those possibilities here because other approaches to time lag determination attempt to use simplex projection and CCM to identify the optimum lag (as defined by highest coefficient values) in systems with no theoretically or empirically predicted lag (see Tsonis, et al., 2015). It is possible, then, that in practice it is worthwhile to sacrifice theoretical rigor in favor of pragmatic applications. To that end, I will briefly present a post hoc analysis which applies simplex projection and CCM[2] to identify the best lag for the out-of-home care entries variable in Clark County.

Simplex projection (see Chapter 5.2.1) is a method developed to distinguish random time series from series which have systematic, patterned behavior in nonlinear environments. Simplex projection associates data points with their nearest neighbors within varying embedding dimensions to determine which dimensionality is appropriate for analysis. A benefit of this method is the production of a coefficient which, similar to a correlation coefficient, describes the relationship between a variable and its nearest neighbors at certain lags. The analysis here in a way turns the simplex analysis described in Chapters 5 and 6 on its side—I am using the method

[2] Because CCM is a bi-variate procedure, I have selected Clark County child welfare court entries as the comparison variable.

not to tune the embedding dimension for a given lag but, instead, look for a maximized coefficient under different lagged conditions. Table 7.1 presents a comparison of the

autocorrelation coefficients with the simplex coefficients along lags one through ten for out-of-home entries in Clark County. We can see that while a lag of seven weeks produced the highest autocorrelation value, it produced the second smallest coefficient value for the observed lags. The maximized simplex coefficient, a lag of three weeks, had a corresponding autocorrelation term that was in the middle in comparison.

Turning to CCM, the method is used to identify weak coupling in nonlinear systems. In the main analysis of this paper CCM was conducted with lag lengths for the outcome variable set in the a priori analysis. Here, like the simplex projection, we vary the lag lengths to look for a maximization of the CCM coefficient. Thus, we are not comparing the raw value of the CCM coefficient when compared to the autocorrelation and simplex coefficients, we are simply looking at the ordering of the lag in comparison to the value of the coefficients. CCM processes for this post hoc analysis were conducted on the bivariate system of out-of-home care entries and dependency court case filings.

Table 7.2: Clark County Out-of-Home Care Entries Lag Lengths and CCM Coefficients

Lag	CCM	Simplex	Autocorrelation
1	0.1982	0.1592	0.1137
2	0.2149	0.1729	0.1143
3	0.2074	0.2294	0.1276
4	0.2177	0.1517	0.1328
5	0.2664	0.1553	0.0958
6	0.2386	0.2073	0.1452
7	0.2235	0.1244	0.1522
8	0.2374	0.1315	0.1250
9	0.2054	0.1626	0.0954
10	0.2776	0.1057	0.0779

Table 7.2 presents the CCM coefficients for lags one through ten, and the corresponding autocorrelation and simplex coefficients for the same lags. As before, the lag applied to the analysis in this dissertation was $\tau=7$, which produced a CCM coefficient of 0.2235. As noted

above, the lag with the maximized simplex coefficient was $\tau=3$. Again, we are presented with lag value that are as distinct from the method applied in this dissertation and though fitting the univariate simplex projection. The highest value for the coefficient occurs at a lag of five, with the lowest values at lags of one, three, and nine. Within the coupled system, there does not appear to be any relationship between the high and low CCM coefficient values when compared to the simplex and autocorrelation coefficients occurring at the same lag.

Both the post hoc analysis using simplex projection and CCM introduce more uncertainty into the lag selection procedure and open questions about how to determine structured lags in systems with no prior information about lag lengths. Even though the procedure for determining lag length which was applied in this dissertation was grounded in both theory and the desire to make some sort of a priori determination of lag structure, I have suggested that the theory might suggest that each individual set of coupled dynamic variables may have its own feedback structure. But such an observation is unsatisfying in the face what amounts to a selection-for-effect in systems where there is no a priori information about lag length. The literature offers no systematic way to approach this problem other than by brute force (see Tsonis, et al., 2015).

In sum, this study found a wide variety of lag lengths in child welfare time series, with no apparent systematic variation among the distribution of those lags. Post hoc analysis suggests that I did not select, using a priori techniques, lag lengths for the maximization of the effect sizes for the methods in this study. An example of this is in Clark County out-of-home care entries: The coefficient determined by the fixed lag ($\tau=7$) in this study was 0.1244. The maximized simplex coefficient, however, was at a lag of three weeks ($\tau=3$) where the value was .2294. This represents a substantial increase in effect size.[3] In spite of the theoretical and methodological difficulties in selecting realistic lag lengths, the approach used in this dissertation did produce some meaningful findings. However, those findings should be read with some caution based on the sensitivity of those outcomes to the setting of lag length.

7.1.2 Patterning in Univariate Systems

Seventy-seven percent (37 out of 48) of the variables[4] in this study population displayed predictable coupled patterning between the variable and its lags. Even though the pattern is not universal, this suggests the existence of some coupling between the present state of a variable and its past states within child welfare systems. Moreover, as the discussion in Part 7.1.1 indicates, the existence of this degree of coupling under the study conditions here lends some credence to the importance of lagged feedback mechanisms in child welfare populations. In other words, I would expect other lag determination methods to produce stronger effect sizes in some variables.[5]

Table 7.3: Effect of Variation of Embedding Dimension on CCM Coefficients

Case A: FE-CF

E	CCM
1	0.3558
2	0.2257
3	0.2235
4	0.2173
5	0.2244
6	0.2218
7	0.2105
8	0.2151
9	0.1900
10	0.1792

Case B: FE-CD

E	CCM
1	0.0022
2	0.0255
3	0.0496
4	0.0065
5	0.0192
6	0.0017
7	0
8	0
9	0
10	0

[3] See Table 7.2.
[4] Seven of the eleven variables which did not display coupling were measures of within-week (i.e., net) population change.
[5] See Table 7.2.

From a practical standpoint, it might be useful to consider what is being captured here. Theory predicts coupled patterned behavior—expressed by an orbit around an attractor—which is governed by rate and criterion terms. In a wholly deterministic system, those rate and criterion terms wholly explain the orbit of the variable and its lagged states around the attractor. What has been identified in this dissertation is that some component—the piece that is described by the coefficient—of the behavior in child welfare systems is describable by those rate and criterion terms in single variable systems (more about bivariate systems in Part 7.1.4). It is that partially deterministic piece which I am calling a population phenomena or a system effect—some of the potential causes for which are discussed in Chapter 2. The effect sizes in the study population are relatively weak.[6] However, because this study uses population data and short time frames the small effect sizes still may be practically significant insofar as child welfare populations are bounded in part by these coupled processes over time. These findings provide some evidence of the nonrandom coupling predicted by Wulczyn (1996), and justify further analysis in a more holistic population frame (Emerson, 1983). As I mentioned in Chapter 6, I am defining any nonzero coefficient as presenting some evidence of nonrandomness in a given time series. Further research, outside of the scope of this dissertation project, is required to assign meaning to the value of the coefficients (see Part 7.4.3, *infra*).

Embedding dimensions can be thought of as folds of an attractor in multidimensional space. The purpose of tuning embedding dimensions is to eliminate the possibility of lower dimensional noise being mistaken for causally patterned behavior. The main point for discussion here, just as in Section 7.1.3 which follows, is the existence of these higher dimensional geometric structures in child welfare time series. The identification of information existing in

[6] This is discussed at greater length in Section 5.2.4, but effect sizes for these coefficients vary greatly across study populations. And because this is a novel application in social sciences, the interpretation of the effect size here is difficult.

higher dimensions in these systems is an important finding from a methodological standpoint because it identifies new dimensions of possibility in studying child welfare phenomena. As child welfare and social work begin to enter into the world of big data, understanding the presence of complex topography in some applications is essential in identifying practically meaningful patterns in big data.

Though the outputs are somewhat sensitive to embedding dimensions, they are considerably less sensitive to embedding when compared to lags. One way to think about this is that lag tuning presents a theoretical problem within a system, whereas embedding dimension simply presents a computational problem. The sensitivity of coefficients to embedding dimensions is described in Table 7.3, which presents two different cases where the lag length is held fixed and the embedding dimension is varied. The coefficients are produced using CCM. In Case A, the coupled system comprises out-of-home care entries and court case filings. The a priori selected embedding dimension was three, which produced a coefficient of 0.2235. With the exception of the coefficient value at the embedding dimension of one, all other coefficient values were approximately similar. In Case B, the coupled system comprises out-of-home care entries and court case closings. The a priori selected embedding dimension was again three, which produced a coefficient of 0.0496. The coefficient in this case was not significantly distinguishable from zero (though close at the p=0.05 level), and along all of the other embedding dimensions the coefficient was either zero or not statistically distinguishable from zero. These two cases are illustrative examples of how coefficients vary across embedding dimensions—there is a slight effect.

Much like mechanistic methods of lag selection (whether autocorrelative or attempting to maximize certain coefficient values), a mechanistic method can be applied for select embedding dimensions for a given outcome variable by simply evaluating the maximum rho value a given lag length of that variable across a number of embedding dimensions. Such a method is much more economical than the analysis applied here and can be implemented by automated algorithm in ways which may produce results which are similar to the more cumbersome method applied herein.

7.1.3 Nonlinearity in Child Welfare Time Series

Nonlinearity is ubiquitous within the child welfare systems in this study, with every variable having a nonlinear component. Moreover, almost sixty percent of the variables in this study displayed a degree of state-dependent nonlinearity which would require nonlinear analytic techniques—more specifically, in these systems linear analysis might mistake systematic behavior for noise. The primary hazard in the treatment of nonlinear time series as linear is underinclusion, that is systematic processes might be written off as noise within the time series when, in fact, that variation contains information along state-dependent nonlinear scales (Bertuglia & Vaio, 2005; Wulczyn, 1996). Thus, looking for nonrandom coupling in the linear world is insufficient to describe the relationship between a variable and its past states when those coupled relationships are nonlinear. The importance of finding nonlinearity is that for nonlinear systems with low-dimensional deterministic components, which includes many of the time series that are the subject of this dissertation, there is the possibility of inferring the behavior of the system by past states through nonlinear modelling techniques once the character of the time series is appropriately identified. This dissertation, then, establishes the presence of state-dependent nonlinearity in some child welfare time series—a novel finding. Because of the limited geographic scope of this study, however, no conclusions can be drawn about where within child welfare time series these nonlinearities can be predictably expected.

7.1.4 CCM Coefficients as Measures of System Effects

As predicted by theory (Wulczyn, 1996) and observed in univariate systems (Part 7.1.2), coupled bivariate systems also display some nonrandom relationships between variables across time. This weak coupling between entries and exits (and openings and closings) detected using CCM support the analysis that a more holistic population frame (Emerson, 1983) may be appropriate for describing some of the variation in child welfare time series. Additionally, the findings from the CCM analysis, specifically the improvement in the prediction of some relationships beyond the prediction in linear models again points to the role that nonlinearity plays in child welfare time series and reinforces the findings analyzed in Part 7.1.3. CCM also provided some support for the hypothesis that the entries and exits into out-of-home care lie within the same mathematical system as case openings and closings in dependency courts. As discussed previously, these findings are conservative given the a priori method of determining lag length and embedding dimension employed in this study.

One area of particular interest in these results is the fact that some of the strongest predictive relationships which were displayed were from the delta (representing a net difference between entries/openings and exits/closings) and the volume (representing a total number of entries plus exits or openings plus closings terms). One interpretation of the influence of these terms is that there is a latent or explicit practice to maintain, as much as possible, a consistent caseload from week-to-week. Though these terms vary in each county system, the CCM results indicate that they have lagged influence on future states of other variables. Thus, it is possible that these terms may act as stand-ins for equilibrium and capacity points. That is, there is some impelling practice within child welfare to attempt to stay (within a constrained time horizon) at a net zero population growth (the delta term) or within some parameter of total case volume (the volume term). This presents interesting opportunities for future research (see Part 7.4.3, *infra*). It is also possible that the strength of these relationships is driven by synchronicity within those time series. Though autorcorrelative synchronicity is sometimes a frustrating problem in time series research, in the case of child welfare that synchronicity, if present, may also serve as an interesting empirical fact. Recalling Chapter 2.1.4 discussing randomness in child welfare systems, the fact that any observed synchronicity exists brings into question whether the system operates in such a way that individual cases are treated independently, or in such a way that individual cases are always treated with reference to system conditions and available system capacity. At a minimum, the results of this dissertation justify further exploration of these population phenomena.

In the dependency court system, analysis identified predictable nonrandom coupling in single variable systems using simplex projection. However, for the main variables, coupled relationships were not identified using CCM. One possible explanation for this result is that there is simply no causal coupling between court case openings and court case closings, whereas those events are related to themselves in relevant ways. Another possible explanation is that the observed univariate systems are displaying synchronicity, and that what is being captured in the simplex analysis is a relationship that is being driven by the underlying demographic etiology of child maltreatment and the system's ability to take in and process those cases. Future research can use comparative drivers to attempt to disentangle the possibility of synchronicity (see Part 7.4.5).

In conclusion, the analysis of child welfare time series as weakly coupled dynamic systems using CCM indicated that population behavior does exist within some time series in some geographies. These results were far from universal even within the sample, and this study provides little support for the idea that system effects are ubiquitous within the population processes of the child welfare system. The limitations (Section 7.3) and future research implications (Section 7.4) of these findings are discussed later in this chapter.

7.2 Summary of Support for Hypotheses

This part presents a summary of the results from Chapter 6 and analysis from Chapter 7 as they relate to the hypotheses presented in Chapter 2.

7.2.1 System Structure Apparent as Nonrandomness

> ***Hypothesis 1****: Structured population behavior in the child welfare system will be apparent as coupled entry and exit dynamics within population-level time series.*

Findings indicate the existence of patterned coupling in eighty-one percent of univariate child welfare time series studied, which provides some support for the theoretically predicted hypothesis that predictable coupling may be a result of population phenomena in some child welfare time series (see Part 7.1.2 and Part 7.1.3). Moreover, in each county the results of this study found coupling between entries and exits within the out-of-home care system, and case openings and closings in dependency court systems—especially among the measures of weekly population change and total weekly volume. Entry-to-exit and opening-to-closing coupling behavior was weaker overall—present in fifteen of twenty-four studied couplings (see Part 7.1.4). The evidence of the bivariate coupling lends some support to the hypothesis, but suggests that the application is limited to some variables within some systems within some geographies. These results suggest qualified support for the first hypothesis.

7.2.2 Coupling Between Out-of-Home Care and Dependency court

> ***Hypothesis 2****: Out-of-home care subsystems and dependency court subsystem interact at the population level and constraints on one*

> *subsystem will manifest themselves in coupled population-level time series for the other subsystem.*

This study found the expected coupling between out-of-home care placements and court case filings—as expected by the policy and practice links in Washington State between those two events. Moreover, there was weak coupling between out-of-home care exits and court case closings in five of the six study counties. Additionally, each study county displayed bidirectional coupling between the delta terms between the out-of-home care and dependency court systems. These results suggest weak and heavily qualified support of the second hypothesis.

7.3 Limitations

This study contains both conceptual and methodological limitations. The three main conceptual limitations are in the operationalization of entries and exits as indicators, the lack of a direct observation of rules-based or resource constraints, and the temporal scope of the project. The main methodological limitations are application to small-N counties and the lag-based tuning of the feedback model. Those matters are discussed in turn.

This dissertation employs an event-based analysis for theorizing population dynamics. Specifically, I use entry/case opening and exit/case closing events as governable factors which relate to child welfare population size, and attempt to model the coupling of those events as what drives the underlying dynamics of the system. However, critical to prior workforce literature in child welfare (Yamatani, et al., 2009; Juby & Scannapico, 2008; Smith & Donovan, 2003) and to the qualitative participants in this study (Chapter 3, *infra*) was the question of workload. Participants noted that workload and caseload are often disjoined, and suggested that an equilibrium state might more appropriately balance around workload than caseload. That is, it is possible that population-based pressures are relieved by adjustments to workload rather than by feedback that associates to entry/exit dynamics.

One reason for the deployment of entry/case opening and exit/case closing events is that they are measured at a granular level over long periods of time. The same longitudinal granularity is not available for workload measures. This same limitation holds true for direct observations of resources or rules-based constraints. Data on money spent, workers allocated, or other resource limitations are not available in the same day-to-day time frame that entry/exit data is available in. The lack of granularity in data which may represent alternative explanations limits the interpretation of y^* and π, and presents a challenge for unpacking the forces which make up those criterions.

Next, I will briefly discuss the problem of scope. Limitations in temporal scope impact both the findings of this dissertation, and interact with the limitations of granularly available data discussed above. Based on the qualitative interviews in Chapter 3, I selected the week as the temporal scope of this study. Beyond the qualitative evidence, my justification for that selection was in wanting to understand the population dynamics at a level as close to the practice of child welfare as possible (if I had been asking broader organizational, budgetary, or policy questions, a different temporal scale—months, quarters, or years—may have been more relevant). Importantly, that decision to limit the study to week-to-week dynamics rendered it impractical to match dynamic effects to other fine-grained statistics (see Tucker & Hurl, 1992). Related to the question of temporal scope is the question of geographic scope. It would have been possible to aggregate the data at levels other than counties, and the dynamics of those higher levels of aggregation may, like questions of temporal scope, shift both the results and the implications. Thus, a limitation of the study of dynamics in this dissertation is its application only to week- and county-level child welfare population dynamics. This limitation is especially important to note because we can expect to reveal different kinds of dynamic information within other scopes (see Wulczyn & Halloran, 2018). The limitation in both temporal and geographic scope presents a challenge for future researchers attempting to locate this coupled behavior in other child welfare time series.

The limitation in scope also presented a limitation for methodology. Because I identified the week as the most relevant aggregate temporal unit, it limited this study to larger county child-welfare systems with sufficient numbers of weekly entries/case openings and exits/case closings to identify patterns. Thus, the results of this study are limited to counties with a certain volume of child welfare cases, which tend to be larger urban or suburban places. Because the county- and unit-level dynamics identified in this study were very heterogeneous, it would be difficult to make broad generalizations, however any generalizable information about the appropriateness of these feedback models must be limited to urban and suburban counties with a regular high weekly volume of child welfare cases. Additionally, though the results for coupled court/out-of-home care dynamics were mostly weak or null, a further limitation of this study is that the relationship between courts and out-of-home care systems is idiosyncratic by state, thus limiting those specific findings to the Washington case.

Section 7.1.1 discusses the importance of proper lag tuning in dynamic feedback models. A significant limitation of this study is in that lag tuning—results of this dissertation are limited to the time lags which were identified for study. Without prior theory or research to guide lag times, a systematic approach was followed. However, due to the sensitivity of later analysis to lag lengths, it is important to note here that if the latent feedback period in child welfare systems is different than those applied in this study then the results of later analyses would differ from those reported here. Section 7.1.1 provides several examples of this impact. Moreover, it is possible that child welfare systems do not have simple coupled lag structures. Instead these systems might have multivariate lags or require some sort of moving average computation. Section 7.5.1 discusses how future methodological research might address refine the use of lag structure in later dynamic time series research. Section 7.5.1 also discusses the need for qualitative study about the process of feedback in street-level systems.

7.4 Implications for Future Research

Two main themes run through my discussion of the implications of this dissertation for future social work research. First, this dissertation provides some empirical support for population thinking in child welfare, and the study of population phenomena must be developed further. Second, because this dissertation identified almost ubiquitous state-dependent nonlinear and higher dimension relationships within child welfare time series, future research which analyzes the trajectories of child welfare populations across time must account for that nonlinearity and dimensionality. With those overarching themes in mind, this section proposes six lines of future research which stem from the findings in this dissertation.

7.4.1 Methodology Related to Lag Determination

As discussed at length in Section 7.1.1, the study of dynamics is dependent in no small part upon appropriately tuning lag lengths. Granular child welfare data presents a methodological challenge here because there is little a priori guidance in setting lags (unlike in other settings, such as population biology and economics where dynamics may follow easily identifiable lag structures). Though there is literature in econometrics related to identifying lag structures empirically (see Enders, 2010), there is an overall weakness in the applied statistics literature in determining lag lengths. In order to prevent lag hacking to generate the most compelling results, methodological development related to lag lengths is necessary (see Ma, et al., 2017). At a minimum, even if it is the simple use of autocorrelation (see Wulczyn & Halloran, 2018), some standard of empirical lag determination should be set for studies in child welfare dynamics.

A component of additional understanding of lag structure in child welfare may be some sort of qualitative research on the street-level process of feedback and response. However, as was mentioned in the qualitative portion of this study, these processes simply may not be observable at the street-level through observation or interview, and may only be able to be identified in the aggregate. Qualitative research focused on the balance of resources and demands may, though, provide more structure within which quantitative study may be performed.

Though not directly related to the question of lag structure, within both the dependency court and out-of-home care systems, the constructed delta variable—representing weekly net change between entries/case openings and exits/case closings—exerted particular influence within systems in all counties and across systems in about half of the counties. This delta term might provide some insight into system equilibrium point, and delta-type equilibriums should be studied.

7.4.2 Predictive Modelling and Forecasting

Though this dissertation uses simplex projection and CCM as analytic tools, both hold the capability of making short-term forecasts of the growth of populations. Such forecasting may be of interest to both policy makers and practitioners in organizing and planning the out-of-home care system (see Russell, 2015). Moreover, the application of predictive EDM holds some promise in overcoming data-availability problems in the child welfare setting (Russell, 2015; Wulczyn, 1996). Specifically, models using EDM tools can make forecast predictions using a relatively small number of critical variables—variables which are generally available at a fine-grain across jurisdictions. Applications of predictive analytics in child welfare settings have been developing over the past several years and have included modelling of placement risk, risk assessment, out-of-home care entry rates, and decision-making support (Benesh, 2017; Schwartz, et al., 2017; Russell & McGill, 2015; Johnson, et al., 2002). More advanced analytic techniques emerging from machine learning (see Benesh, 2017) and applications of EDM tools are being developed to make them more policy relevant (see Cyrus, 2014).

7.4.3 Systems Effects Coefficients as Predictors

This dissertation found a high degree heterogeneity in both simplex projection and CCM coefficients both among and between the out-of-home care and dependency court systems. Even though the present study was limited by a narrow geographic scope, the degree of heterogeneity suggests some possibility that s-mapping and CCM coefficients may be used to explain geographic variation as partially explained by the effects of population phenomena or other systems effects across geographies. This moves these coefficients from the left to the right side of the equation as a measure of system effect or system structure. The potential application is in any observed child welfare setting which varies geographically.

7.4.4 Hierarchical Analysis

Billari (2015) discusses the integration of macro- and micro-level processes in demographic research. Interestingly, and applicable here, is the idea that population-exit phenomena could hold the key to integrating hierarchical analysis. As briefly discussed in Part 7.4.3, using coefficients as predictors is one application which may link macro- and micro-level analysis. However, the significance of hierarchical analysis for CCM in the child welfare setting extends beyond that application. One of the limitations of this study is its temporal and geographic scope. Many of those limitations turn out to be advantages if you can create hierarchies—temporal or geographic—of these dynamic models. Hierarchical modeling might provide insight into separating policy effects from practice effects, by capturing the contributing component of system effect at each level of analysis. This application could be particularly useful in an identifying differential uptake of population-focused policies. Additionally, situating temporal dynamics hierarchically (weeks within months within years, for example) might lead to insight into differential drivers of population effects based on structure created in practice, in organizations, and by policy. Methodologies for hierarchical analysis for CCM are presently being developed for applications in fisheries research (Stephen B. Munch, personal communication, June 29, 2017).

7.4.5 Differentiation of Drivers

One of the powers of convergent cross mapping is its ability to differentiate causally between drivers of observed behavior. As I have stated earlier in this dissertation, I believe that entry/case opening/exit/case closing dynamics are likely, in addition to having direct effects, most significant as indicators of other underlying causal forces. CCM can be applied to test alternative (and alternative directional) causal explanations and provide insight into the strength of the underlying effect in comparison to other potential causes. This provides a potential alternative to differentiating demographic drivers in time series using least squared regression (Swann & Sylvester, 2006; Paxson & Waldfogel, 2003; Blank, 2001). For example, CCM would be well suited to compare alternative explanations of entry dynamics which focus on case exits compared to workload. The key here is the availability, at a fine-grained temporal and geographic level, of data which describe alternative explanations.

7.4.6 Relative Judgments

This dissertation does not address the potential of relative judgments as a regulatory mechanism for entry and exit dynamics (Libovitch 2017; Grogan-Kaylor, 2000). However, this dissertation raises an important question related to the existence of those relative judgments. If what has been measured here is a systems effect, as I believe that it is, then we know that there is some degree of behavior in the child welfare system which may be attributable to something other than that atomistic review of individual cases. The systems effects found in this dissertation again highlight the holism of child welfare caseload (Emerson, 1983), and the hazard of neglecting caseload dynamics which my relating directly to shifting frames of reference; ideas about risk, responsibility, and sanctions; and other discretionary moves to relieve caseload pressure. While there is qualitative evidence of these street-level bureaucracy type phenomena (see Smith & Donovan, 2003), the emerging econometrics of relative judgments present an opportunity for a new research direction for child welfare as it relates to both the out-of-home care and dependency court systems (Libovitch, 2017; Depew, Eren, and Mocan, 2016; Eren and Mocan, 2016; Libovitch, 2016).

7.5 Social Work Policy and Practice Implications

The results of this study have practice implications for child welfare administrators and policymakers whose jobs include broadly setting the resource geographies in which child welfare operates. Population thinking applies and is consequential, and approaching the problem of resource allocation in child welfare from a population standpoint could be beneficial. This dissertation demonstrates the usefulness of employing a systems conception to describe how constraints shape child welfare practice. Importantly, results of this study explain the observed dynamics in child welfare populations, in part, through resource availability in child welfare practice. The theoretical implication of this is that child welfare professionals are responding to resource constraints in a way that may prevent them from focusing their decision making on the facts and context of a single case. Thus, if this inference is correct, if child welfare administrators and policymakers want front-line workers to make decisions rooted in the needs of individual clients then some administrative and policy focus must be dedicated to addressing the system factors that result in the behavior observed in this study.

This is an exploratory study, so the practical guidance for how systems factors may be addressed by child welfare administrators and policymakers is limited and will require additional research to really provide concrete plans of action. However, I want to suggest two areas of focus. First, general awareness of systems effects. This dissertation provides an extended discussion of a way to conceptualize child welfare in the context of populations, and illustrates ways in which systems may behave distinctly from individuals and distinctly from individuals who make up a population. Thinking in systems is an important avenue for administrators and policymakers (see Meadows, 2008). Systems thinking provides different ways of thinking about the limitation of and misallocation of resources that is worth the consideration of administrators and policymakers.

Finally, and most concretely, alternative forecasting models which employ systems thinking may provide value to policymakers and child welfare administrators. The value of short term prediction to on-the-ground work likely merits attention. Though not discussed at length in this dissertation, in addition to being an analytical method EDM is also a method suited for short term forecasting. Short term forecasting could be useful to child welfare agencies and to dependency court schedulers in more closely matching human resources and temporal resources to the fluctuations in demand. The results of this dissertation generally support the use of EDM to make short-term predictions[7] (with a scope of weeks or months) about the changes in child welfare populations. Specifically, EDM can be used to project the number of out-of-home care entries over a period of weeks and to give a measure of the scope of utility of those predictions.

[7] Using either nearest neighbors in simplex projection, or global univariate (s-mapping) or bivariate (CCM) time series with weights given to local points.

Though the results of this dissertation do temper that application somewhat (given the weakness of the coupling and the narrowness of the time scope), the novel application of EDM and the support for its detection of predictable population processes will be of some use for short-term planning by policy makers and practitioners. This potential application will require additional empirical and translational work in order to be clearly practice relevant. Moreover, the use of predictive EDM in a novel setting may be enhanced by further refinement of the methodology over varying temporal and geographic scopes (see Section 7.3). One of the advantages presented by EDM, however, is that unlike other predictive models, analysis can be conducted with a minimal number of variables. The practical implication of this is that EDM may provide a more nimble and responsive forecasting method when compared to some predictive models which may contain more than one hundred different variables.

7.6 Conclusion

This dissertation expands upon prior theoretical work to produce an empirical study of dynamics within child welfare populations. This dissertation is unique in its focus on dynamic child welfare time series, and employs a nonparametric methodology novel to social work research. It provides some support for the application of population theory to the growth and stability of child welfare populations. It identifies consequential nonlinearities in child welfare time series. It provides empirical support for the application of nonlinear population growth models. Child welfare researchers should consider the questions of state-dependent nonlinearity, higher dimensionality, and population effects when working with time series data. Though the primary contribution of this dissertation is as primary empirical research, it highlights the importance of population effects on child welfare policy and practice.

REFERENCES

Abbott, Andrew (2016). Processual Sociology. Chicago, IL: University of Chicago Press.

Abbott, A. (2004). Introduction to heuristics. Chicago, IL: University of Chicago Press.

Albers, E., Reilly, T., and Rittner, B. (1993). Children in foster care: Possible factors affecting permanency planning. *Child and Adolescent Social Work Journal*, 10(4), 329.

Anderson, R., and May, R. (1991). Infectious diseases of humans. Oxford, UK: Oxford Science Publications.

Almeida, A., Ramos, V., Almeida, H., Escobar, C., and Garcia, C. (2017). Analysis of contextual variables in the evaluation of child abuse in the pediatric emergency setting. *Journal Pediatria*, 93(4), 374–81.

Alwon, F., and Reitz, A. (2000). Empty chairs: The workforce crisis in child welfare. Washington, D.C.: The Child Welfare League of America.

Ariew, A. (2008). Population thinking. In Ruse, M. (ed.) The Oxford Handbook of the Philosophy of Biology. Oxford, UK: Oxford University Press.

Babones, S. (2015). Interpretative quantitative methods for the social sciences. *Sociology*, 50(3), 453–69.

Barth, R. (1997). The value of special needs adoption. In Avery, R. (ed.), ADOPTION POLICY AND SPECIAL NEEDS CHILDREN. Auburn House: New York.

Barth, R., Wulczyn, F., and Crea, T. (2004–2005). From anticipation to evidence: Research on the Adoptions and Safe Families Act. *The Virginia Journal of Social Policy and the Law*, 12, 371.

Berger, L. (2004). Income, family structure, and child maltreatment risk. *Children and Youth Services Review*, 26(8), 725–48.

Barth, R. (1997). The value of special needs adoption. In Avery, R. (ed.), Adoption Policy and Special Needs Children. Auburn House: New York.

Barron, D., West, E., and Hannan, M. (1994). A time to grow and a time to die: growth and mortality of credit unions in New York City, 1914–1990. *American Journal of Sociology*, 100(2), 381–421.

Baumann, D., Fluke, J., Dalgleish, L., and Kern, H. (2014). The decision-making ecology. In Shlonsky, A., and Benbenishty, R. (eds.) From Evidence to Outcomes in Child Welfare: An International Reader. New York, NY: Oxford University Press.

Benedict, M., and White, R. (1991). Factors associated with foster care length of stay. *Child Welfare*, 70(1), 45–58.

Benesh, A. (2017). *Predicting Child Welfare Future Placements for Foster Youth: An Application of Statistical Learning to Child Welfare* (Doctoral dissertation). Available from ProQuest Dissertations & Theses Global (10258386).

Berry, B., and Kasarda, J. (1977). Contemporary urban ecology. New York, NY: Macmillan.

Bertuglia, C., and Vaio, F. (2005). *Nonlinearity, chaos, and complexity: the dynamics of natural and social systems*. Oxford, UK: Oxford University Press.

Billari, F. (2015). Integrating macro- and micro-level approaches in the explanation of population change. *Population Studies*, 69(S1), S11–20.

Blank, R. (2001). What causes public assistance caseloads to grow? *Journal of Human Resources*, 36(1), 85–118.

Brann, E. (2011). The logos of Heraclitus. Philadelphia, PA: Paul Dry Books.

Brekke, J. (2012). Shaping a science of social work. *Research on Social Work Practice*, 25(5), 455-464.

Bronfenbrenner, U. (1979). The ecology of human development. Boston, MA: Harvard University Press.

Bottomore, T. B. (2010). Sociology: A guide to problems and literature. London, UK: Routledge Revivals

Brauer, F. (2005). The Kermack-McKendrick epidemic model revisited. *Mathematical Biosciences*, 198, 119–31.

Brauer, F., and Castillo-Chavez, C. (2012). Mathematical models in population biology and epidemiology (2nd edition). New York, NY: Springer.

Brodkin, E. (2011). Policy work: street level organizations under new managerialism. *Journal of Public Administration Research and Theory*, 21(suppl. 2), i253–77.

Brodkin, E. (2008). Accountability in street-level organizations. *International Journal of Public Administration*, 31(3), 317–36.

Brodkin, E. (2006). Bureaucracy redux: management reformism and the welfare state. *Journal of Public Administration and Theory*, 17(1), 1–17.

Brunton, S., Proctor, J., and Kutz, J. (2015). Discovering governing equations from data by sparse identification of nonlinear dynamical systems. *Proceedings of the National Academy* *of Science of the United States of America*, 113(15), 3932–37.

Butler, B. (1977). Presiding judges' role perceptions of trial court administrators. *The Justice System Journal*, 3(2), 181.

Carroll, G., and Hannan, M. (1989). Density dependence in the evolution of populations of newspaper organizations. *American Sociological Review*, 54(4), 524–41.

Carroll, G., and Huo, Y. (1986). Organizational task and institutional environments in ecological perspective: findings from the local newspaper industry. *American Journal of Sociology*, 91(4), 838–73.

Carbone-Lopez, K., and Lauritsen, J. (2013). Seasonal variation in violent victimization: Opportunity and annual rhythm of the school calendar. *Journal of Quantitative Criminology*, 29(3), 399–422.

Carnochan, S., Taylor, S., Abramson, A., Han, M., Rashid, S., Maney, J., Taylor, S., Teuwen, S., & Austin, M. J. (2006). Child welfare and the courts: An exploratory study of the relationship between two complex systems. *Journal of Public Child Welfare*, 1(1), 117—36.

Clark, A., Ye, H., Isbell, F., Deyle, E., Cowles, G., Tilman, D., and Sugihara, G. (2015). Spatial convergent cross mapping to detect causal relationships from short time series. *Ecology*, 96(5), 1174–81.

Cobey, S., Baskerville, E. (2016). Limits to causal inference with state-space reconstruction for infectious disease. PLoS ONE 11(12), 1–22.

Coulson, T., and Godfray, C. (2007). In May, R., and McLean, A. (eds.), Theoretical Ecology (3rd Ed.). Oxford, UK: Oxford University Press.

Coulton, C., Crampton, D., Irwin, M., Spilsbury, J., & Korbin, J. (2007). How neighborhoods influence child maltreatment: a review of the literature and alternative pathways. *Child Abuse and Neglect*, vol. 31, 1117–1142.

Courtney, M. (1998). The costs of child protection in the context of welfare reform. *The Future of Children*, 8(1), 88.

Courtney, M. (1995). Reentry to foster-care of children returned to their families. *Social Service Review*, 69(2), 226–41.

Courtney, M and Hook, J. (2012). Evaluation of the impact of enhanced parental legal representation on the timing of permanency outcomes for children in foster care. *Children and Youth Services Review*, 34, 2263.

Courtney, M., and Wong, Y. (1996). Comparing the timing of exits from substitute care. *Children and Youth Services Review*, 184(4–5), 307–34.

Depew, B., Eren, O., and Mocan, N. (2016). *Judges, juveniles and in-group bias* (No. w22003). National Bureau of Economic Research Working Paper Series.

Deyle, E., Maher, M., Hernandez, R., Basu, S., and Sugihara, G. (2016). Global environmental drivers of influenza. *Proceedings of the National Academy of Sciences*, 113(46), 13081–86.

Dost, F. (2015). A non-linear causal network of marketing channel system structure. *Journal of Retailing and Consumer Services*, 23, 49–57.

Dost, F., and Maier, E. (2017). E-Commerce effects on energy consumption: A multi-year ecosystem-level assessment. *Journal of Industrial Ecology*, doi: 10.1111/jiec.12639

Duncan, O. (1964). Social organization and the ecosystem. In Faris, R. (ed.) Handbook of modern sociology. Chicago, IL: Rand McNally.

Duquette, D. (2000). Legal representation for children in protection proceedings: two distinct lawyer roles are required. *Family Law Quarterly*, 34(3), 441–66.

Duquette, D., and Haralambie, A. (eds.) (2010). Child welfare law and practice. Denver, CO: Bradford Publishing Co.

Ellett, A., Ellis, J., Westbrook, T., and Dews, D. (2007). A qualitative study of 369 child welfare professionals' perspectives about factors contributing to employ retention and turnover. *Children and Youth Services Review*, 29(2), 264.

Emerson, R. (1983). Holistic effects in social-control decisionmaking. *Law & Society Review*, 17, 425.

Enders, W. (2010). Applied Econometric Time Series (3rd ed.) Hoboken, NJ: John Wiley & Sons.

Eren, O., and Mocan, N. (2016). *Emotional judges and unlucky juveniles* (No. w22611). National Bureau of Economic Research Working Paper Series.

Evans, A., Singh, N., Friebe, A., Arnerno, J., Laske, T., Frobert, O., Swenson, J., and Blanc, S. (2016). Drivers of hibernation in the brown bear. *Frontiers in Zoology*, 13(7), 1–13.

Forrester, J. (1995). *The Counterintuitive Behavior of Social Systems*, The Collected Papers of Jay W. Forrester (1995).

Forrester, J. (1994). Systems dynamics, systems thinking, and soft OR. *Systems Dynamics*, 10, 245.

Forrester, J. (1969). Urban Dynamics. Cambridge, Mass: Massachusetts Institute of Technology Press.

Foster-Fishman, P., Nowell, B., and Yang, H. (2007). Putting the system back into systems change: A framework for understanding and changing organizational and community systems. *American Journal of Community Psychology*, 39, 197–215.

Freeman, J., Carroll, G., and Hannan, M. (1983). The liability of newness: age dependence in organizational death rates. *American Sociological Review*, 48(5), 692–710.

Frigg, R. (2004). In what sense is the Kolmogorov-Sinai Entropy a measure for chaotic behaviour? Bridging the gap between dynamical systems theory and communication theory. *British Journal for the Philosophy of Science*, 55(3), 411–34.

Furlan, C., Diniz, C., and Franco, M. (2010). Estimation of lag length in distributed lag models: A comparative study. *Advance Applied Statistics*, 17(2), 127–142.

Gallas, E. (1967). The planning function of the court administrator. *Judicature*, 50(8), 268.

Green, D., & McDermott, F. (2010). Social work from inside and between complex systems: perspectives on person-in-environment for today's social work. *The British Journal of Social Work*, 40(8), 2414–30.

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37, 424–38.

Grogan-Kaylor, A. (2000). *The effect of population level characteristics of the foster care caseload on reunification from foster care* (Doctoral dissertation). Available from ProQuest Dissertations & Theses Global (304635090).

Hannan, M. (1978). Models for change in quantitative variables, part I, deterministic models. In Technical Report #63. Palo Alto California: Laboratory for Social Research, Stanford University.

Hannan, M., & Freeman, J. (1987). The ecology of organizational founding: American labor unions, 1836–1985. *American Journal of Sociology*, 92(4), 910–43.

Hannan, M., & Freeman, J. (1977). The population ecology of organizations. *American Journal of Sociology*, 82(5), 929–64.

Hansen, ME, and Hansen, B. (September, 2005). The economics of the adoption of children from foster care. American University, Washington DC, Department of Economics, Working Paper Series 2005-10.

Hastings, H., Pekelney, R., Monticciolo, R., vun Kannon, D., and Del Monte, D. (1982). Time scales, persistence, and patchiness. *Biosystems*, 15(4), 281–89.

Huffaker, R., Canavari, M., Munoz-Carpena, R. (in press 2017). Distinguishing between endogenous and exogenous price volatility in food security assessment: An empirical nonlinear dynamics approach. *Agricultural Systems*.

Huffaker, R., and Fearne, A. (2014). Empirically testing for dynamic causality between beer promotions and sales in England. *Proceedings in Food System Dynamics*, 2014, 270–274.

Irvin, J., Spokoyny, D., and Martin, F. (2016). Dynamical systems modeling of the child-mother dyad: Causality between child-directed language complexity and language development. In Papafragou, A., Trueswell, J., Grodner, D., and Mirman, D. (eds.), Proceedings of the 38th Annual Conference of the Cognitive Science Society. Cognitive Science Society.

Jeavons, T., and Cnaan, R. (1997). The formation, transitions, and evolution of small religious organizations. *Nonprofit and Voluntary Sector Quarterly*, 26(4), S62–84.

Johnson, M., Hendricks Brown, C., and Wells, S. (2002). Using Classification And Regression Trees (CART) to support worker decision making. *Social Work Research*, 26(1), 19–29.

Jones, L. (1993). Decision making in child welfare: A critical review of the literature. *Child and Adolescent Social Work Journal*, 10(3), 241.

Juby, C., and Scannapieco, M. (2007). Characteristics of workload management in public child welfare agencies. *Administration in Social Work*, 31(3), 95–109.

Keitt, T.H. & Stanley, H.E. (1998). Dynamics of North American breeding bird populations. *Nature*, 393, 257–260.

Kemp, S., and Bodonyi, J. (2002). Beyond termination: length of stay and predictors of permanency for legally free children first placed as infants. *Child Welfare*, 81(1), 58–86.

Kirk R., Kirk, D., and Pesheck, P. (2016) Decision making for complex ecosystems: A technique for establishing causality in dynamic systems. In Stephanidis C. (eds.) HCI International 2016—Extended Abstracts. HCI 2016. Communications in Computer and Information Science, vol 617. Springer.

Krieger, N. (2011). Epidemiology and the people's health. New York, NY: Oxford University Press.

Lansing, S. (2001). Estimating the effect of targeted enforcement strategies on conviction and imprisonment rates. Paper presented at the Nineteenth International Conference of the Systems Dynamics Society. Available at: http://www.systemdynamics.org/conferences/2001/papers/Lansing_1.pdf

Leibovitch, A. (2017). Punishing on a curve. *Northwestern University Law Journal*, 111(5), 1205–80.

Leibovitch, A. (2016). Relative judgments. *The Journal of Legal Studies*, *45*(2), 281–330.

Lens, V., Cary Katz, C., and Suarez, K. (2016). Case workers in family court: A therapeutic jurisprudence analysis. *Children and Youth Services Review*, 68, 107–114.

Lin, A. (1998). Bridging positivist and interpretivist approaches to qualitative methods. *Policy Studies Journal*, 26(1), 162–80.

Lippincott, R., and Stoker, R. (1992). Policy design and implementation effectiveness: structural change in a county court system. *Policy Studies Journal*, 20(3), 376–87.

Lipsky, M. (2010). *Street-level bureaucracy, 30th ann. Ed.: dilemmas of the individual in public service*. New York, NY: Russell Sage Foundation.

Lopez, L. and Zuniga, R. (2014). Dynamics of judicial service supply chains, *Journal of Business Research*, 67(7), 1447.

Lopez, L. and Porfirio, G. (2009). Judicial process dynamics. Paper presented at the Twenty-Seventh International Conference of the Systems Dynamics Society. Available at: http://www.systemdynamics.org/conferences/2009/proceed/papers/P1370.pdf

Lorenz, E. (1963). Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences*, 20(2), 130–41.

Luo, C., Zheng, X., and Zeng, D. (2014). Causal inference in social media using convergent cross mapping. *Proceedings of the Intelligence and Security Informatics Conference, 2014 IEEE Joint*, 260–263.

Ma., H., Leng, S., Tao, C., Ying, X., Kurths, J., Lai, Y., and Lin, W. (2017). Detection of time delays and directional interactions based on time series from complex dynamical systems. *Physical Review*, 96(012221), 1–8.

Maher, M. (2014). *Harnessing change: Human health through the lens of evolution and dynamical systems theory* (Doctoral dissertation). Available from ProQuest Dissertations & Theses Global (3681211).

Massinga, R., and Pecora, P. (2004). Providing better opportunities for older children in the child welfare system. *The Future of Children*, 14(1), 150.

Mayer, K. (1962). Developments in the study of population. *Social Research*, 29(3), 293–320.

Meadows, D. (2008). Thinking in Systems: A Primer. New York, NY: Chelsea Green Publishers.

Meyer, C. (1983). Clinical Social Work in the Eco-Systems Perspective. New York, NY: Columbia University Press.

McCold, P. (1993). *The role of fiscal policy in producing prison population dynamics: A trend analysis and dynamic simulation of felony offender processing in New York State*. (Doctoral dissertation). Available from Rockefeller College of Public Affairs and Policy, Albany, New York.

Murphy, S., and Goodson, J. (2007). Numbers alone do not tell the whole story: a program evaluation designed to generate evidence-based knowledge and practice in child welfare supervision. *Journal of Evidence-Based Social Work*, 4(3/4), 81–101.

Nielsen, F., and Hannan, M. (1977). The expansion of national education systems: tests of a population ecology model. *American Sociological Review*, 42(3), 479–90.

Olsen, L. (1982). Predicting the permanency status of children in foster care. *Social Work Research Abstracts*, 18(1), 9.

Outley, A. (2005). Overcoming barriers to permanency: Recommendations for juvenile and family courts. *Family Court Review*, 44(2), 244.

Patton, M. (2001). *Qualitative evaluation and research methods* (3rd ed.). Newbury Park, CA: Sage Publications.

Paxon, C., and Waldfogel, J. (2003). Welfare reforms, family resources, and child maltreatment. *Journal of Policy Analysis and Maltreatment*, 22(1), 85.

Pejić-Bach, M and Čerić, V. (2006). Developing systems dynamics models with a step-by-step approach. *Journal of Informational and Organizational Sciences*, 31, 171.

Penrose, EF. (1934). Population theories and their application: with special reference to Japan. Stanford, CA: Stanford University Press.

Peters, C. (2012). Examining regional variation in extending foster care beyond 18: Evidence from Illinois. *Children and Youth Services Review*, 34, 1710.

Perretti, C., Munch, S., and Sugihara, G. (2013). Model-free forecasting outperforms the correct mechanistic model for simulated and experimental data. *Proceedings of the National Academy of Sciences*, 110(13), 5253–57.

Proctor, E., Knudsen, K., Fedoravicius, N., Hovmand, P., Rosen, A., and Perron, B. (2007). Implementation of evidence-based practice in community behavioral health: agency director perspectives. *Adm. Policy Mental Health*, 34, 479–88.

Purcell, E. (2003). Caseload burdens and jurisdictional limitations: some observations from the history of the Federal Courts. *New York University School of Law Review*, 46, 7–28.

Rea, W., Oxley, L., Reale, M., Brown, J. (2009). Estimators of Long-Range Dependence: An Empirical Study. *Electronic Journal of Statistics*, 0, 0–16.

Resnik, J. (1982). Managerial judges. *Harvard Law Review*, 96(2), 374–448.

Richmond, M. (1917). Social diagnosis. New York, NY: Russell Sage Foundation.

Robel, L. (1990). Caseload and judging: judicial adaptions to caseload. *Brigham Young University Law Review*, 1990(3), 3–65.

Roux, A. (2004). The study of group-level factors in epidemiology: rethinking variables, study designs, and analytical approaches. *Epidemiologic Reviews*, 26, 104–11.

Russell, J. (2015). Predictive analytics and child protection: constraints and opportunities. *Child Abuse and Neglect*, 46, 182–89.

Russell, J., and MacGill, S. (2015). Demographics, policy, and foster care rates: a predictive analytics approach. *Children and Youth Services Review*, 58, 118–26.

Scarcella, C. A. (2006). The cost of protecting vulnerable children V: Understanding state variation in child welfare financing. Washington, D.C.: The Urban Institute.

Scarcella, C. A. (2004). The cost of protecting vulnerable children IV: How child welfare funding fared during the recession. Washington, D.C.: The Urban Institute.

Schiecke, K., Pester, B., Feucht, M., Leistritz, L., and Witte, H. (2015). Convergent Cross Mapping: Basic concept, influence of estimation parameters, and practical application. *Proceedings of the Engineering in Medicine and Biology Society*, *2015 IEEE 37th Annual International Conference*, 7418–21.

Schwartz, I., York, P., Nowakowski-Sims, E., and Ramos-Hernandez, A. (2017). Predictive and prescriptive analytics, machine learning and child welfare risk assessment: the Broward County experience. *Children and Youth Services Review*, 81, 309–20.

Simpson, D., Imrey, P., Geling, O., and Butkus, S. (2000). Statistical estimation of child abuse rates from administrative databases. *Children and Youth Services Review*, 22(11/12), 951–71.

Smith, B. and Donovan, S. (2003). Child Welfare Practice in Organizational and Institutional Context. *Social Service Review*, 77, 553.

Smith, CJ., Rudolph, C., and Swords, P. (2002). Kinship care: Issues in permanency planning. *Children and Youth Services Review*, 24(3), 175.

Stein, T. and Rzepnicki (1984). Decisionmaking in child-welfare services: intake and planning. Hingham, MA: Kluwer Academic Publishing.

Stenseth, N. (1999). Population cycles in voles and lemmings: density dependence and phase dependence in a stochastic world. *Oikos*, 87, 427.

Stenseth, N., Falck, W., Chan, K., Bjornstad, O., O'Donoghue, M., Tong, H., Boonstra, R., Boutin, S., Krebs, C., and Yoccoz, N. (1998). From patterns to processes: phase and density dependence in the Canadian Lynx cycle. *Proceedings of the National Academy of Sciences of the United States of America*, 95(26), 15430.

Stinchcombe, A. (1977). On the virtues of old institutionalism. *Annual Review of Sociology*, 23(1), 1–18.

Stinchcombe, A. (1965). Social structure and organizations. In March, J. (ed.), Handbook of Organizations. New York, NY: Rand McNally & Co.

Soetaert, K., Petzoldt, T., and Setzer, R. (2010). Solving differential equations in R: package deSolve. *Journal of Statistical Software*, 33(9), 1–25.

Sugihara, G. (1994). Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. *Nature*, 334, 734–41.

Sugihara, G., et al., (2012). Detecting causality in complex ecosystems. *Science*, 338, 496–500.

Sugihara, G., Grenfell, B., May, R. (1990). Distinguishing error from chaos in ecological time series. *Philosophical Transactions: Biological Sciences*, 300(1257), 235–51.

Suigihara, G., and May, R. (1990). Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. *Nature*, 344, 477–95.

Swann, C., and Sylvester, M. (2006). The foster care crisis: what caused caseloads to grow? *Demography*, 43(2), 309–35.

Takens, F. (1981). Detecting strange attractors in turbulence. *Lecture Notes in Mathematics*, 898(1), 366–81.

Testa, M. (2004). When children cannot return home: Adoption and guardianship. *The Future of Children*, 14(1), 115.

Thompson, J. (1967). Organizations in action: social science bases of administrative theory. New York: McGaw-Hill.

Tsonis, A., Deyle, E., May, R., Sugihara, G., Swanson, K., Verbeten, J., & Wang, G. (2015). Dynamical evidence for causality between galactic cosmic rays and interannual variation in global temperature. *Proceedings of the National Academy of Sciences*, *112*(11), 3253–56.

Tucker, D. (1996). Eclecticism is not a free good: barriers to knowledge development in social work. *Social Service Review*, 70(3), 400–34.

Tucker, D., Hurl, L., and Ford, H. (1994). Applying organizational ecology to the family: the case of who persists in providing foster care. *Journal of Marriage and Family*, 56(4), 1005–18.

Tucker, D., and Hurl, L. (1992). An ecological study of the dynamics of foster home entries. *Social Service Review*, 66(4), 617–41.

Tucker, D., and MacKenzie, M. (2012). Attachment theory and change processes in foster care. *Children and Youth Services Review*, 34, 2208–19.

Tuma, N., and Hannan, M. (1984). *Social Dynamics: Models and Methods*. New York, NY: Academic Press.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2015). Child maltreatment 2013.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2013). Child maltreatment 2012.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2012). Child maltreatment 2011.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2011). Child maltreatment 2010.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2010). Child maltreatment 2009.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2010). Child maltreatment 2008.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2009). Child maltreatment 2007.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2008). Child maltreatment 2006.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2007). Child maltreatment 2005.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2006). Child maltreatment 2004.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2005). Child maltreatment 2003.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2004). Child maltreatment 2002.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2003). Child maltreatment 2001.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2002). Child maltreatment 2000.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2001). Child maltreatment 1999.

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2014a). Number of children entering foster care by state, FY2004–FY2013. Retrieved from http://www.acf.hhs.gov/sites/default/files/cb/entering_foster_care2013.pdf

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2014b). Number of children exiting foster care by state, FY2004–FY2013. Retrieved from http://www.acf.hhs.gov/sites/default/files/cb/exiting_foster_care2013.pdf

U.S. Department of Health and Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau. (2014c). Number of children in foster care by state, FY2004–FY2013. Retrieved from http://www.acf.hhs.gov/sites/default/files/cb/children_in_care_2013.pdf

VanMeter, S. (2004). Public access to juvenile dependency proceedings in Washington State: An important piece of the permanency puzzle. *Seattle University Law Review*, 27, 859–97.

Verma, A., Garg, A., Blaber, A., Fazel-Rezai, R., and Tavakolian, K. (2016). Analysis of causal cardio-postural inaction under orthostatic stress using Convergent Cross Mapping. *Proceedings of the Engineering in Medicine and Biology Society*, *2016 IEEE 38th Annual International Conference*, 2319–2322.

Washington State Office of Public Defense (2018). Parental Representation Program. Retrieved from https://www.opd.wa.gov/program/parents-representation

Wismüller, A., Abidin, A., Dsouza, A., and Nagarajan, M. (2016) Mutual connectivity analysis (MCA) for nonlinear functional connectivity network recovery in the human brain using Convergent Cross-Mapping and non-metric clustering. In Merényi, E., Mendenhall, M., and O'Driscoll P. (eds,), *Advances in Self-Organizing Maps and Learning Vector Quantization. Advances in Intelligent Systems and Computing*, 428. Springer.

Wulczyn, F. (1996). A statistical and methodological framework for analyzing the foster care experiences of children. *Social Services Review*, 70, 318.

Wulczyn, F. (1986). *Child welfare caseloads: A sociological interpretation* (Order No. T-30072). Available from ProQuest Dissertations & Theses Global (303521793).

Wulczyn, F., Daro, D., Fluke, J., Feldman, S., Glodek, C., and Lifanda, K. (2010). Adopting a Systems Approach to Child Protection: Key Concepts and Considerations, United Nations Children's Fund Working Paper, available at http://www.chapinhall.org/sites/default/files/Adapting_A_Systems_Approach.pdf

Wulczyn, F., and Halloran, J. (2017). Modeling complexity in human-built systems: new approaches, new findings in foster care. *Journal of Policy and Complex Systems*, 3(2), 105–119.

Wulczyn, F., and Halloran, J. (2017). Foster care dynamics and systems science: implications for policy and research. Manuscript submitted for publication.

Wulczyn, F., Kogan, J., and Dilts, J. (2001). The effect of population dynamics on performance management. *Social Service Review*, 75(2), 292–317.

Yamatani, H., Engel, R., and Spjeldnes, S. (2009). Child welfare caseload: what's just right? *Social Work*, 54(4), 361–368.

Yao, L. (2017). Causative impact of air pollution on evapotranspiration in the North China Plain. *Environmental Research*, 158, 436–42.

Ye, H., Beamish, R., Glaser, S., Grant, S., Hsieh, C., Richards, L., Schnute, J., and Sugihara, G. (2015). Equation-free mechanistic ecosystem forecasting using empirical dynamic modeling. *Proceedings of the National Academy of Science of the United States of America*, 112(13), E1569–E1576.

Ye, H., Deyle, E., Gilarranz, L., and Sugihara, G. (2015). Distinguishing time-delayed causal interactions using convergent cross mapping. *Nature Scientific Reports*, 5(14750), 1–9.

Zivot, E., & Wang, J. (2006). Modeling Financial Time Series with S-Plus (2^{nd} ed.). New York, NY: Springer-Verlag.

APPENDICIES

APPENDIX A: SUMMARY STATISTICS

Clark County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	12	11	23	0	5	4	10	1
Standard Deviation	5	5	8	6	4	4	5	5
Median	11	11	22	0	5	4	9	1
Mode	11	12	19	0	3	0	8	-2
Minimum	0	1	5	-16	0	0	0	-22
Maximum	32	30	54	24	21	24	30	21

King County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	21	22	43	-1	14	15	29	-1
Standard Deviation	7	8	12	9	6	7	9	9
Median	20	21	42	0	14	14	29	-1
Mode	19	18	43	0	11	11	32	1
Minimum	5	2	11	-35	0	1	3	-27
Maximum	49	53	84	28	37	43	62	29

Pierce County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	20	20	39	0	11	10	21	1
Standard Deviation	7	7	11	9	6	7	9	8
Median	19	19	39	1	10	9	20	1
Mode	19	19	37	-1	9	6	17	1
Minimum	3	3	10	-39	0	0	3	-33
Maximum	43	52	82	33	45	44	60	36

Snohomish County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	11	11	23	0	9	9	18	0
Standard Deviation	5	6	8	8	5	5	7	7
Median	11	10	22	0	8	8	17	0
Mode	13	8	21	-3	7	7	18	0
Minimum	1	0	4	-35	0	0	1	-27
Maximum	33	47	59	25	28	35	49	21

Spokane County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	14	14	28	0	10	9	19	1
Standard Deviation	5	6	8	7	5	5	8	6
Median	14	14	28	0	9	9	19	1
Mode	12	13	29	4	5	6	17	1
Minimum	1	2	7	-32	0	0	2	-39
Maximum	34	35	62	22	26	46	53	25

Yakima County

	Out-of-Home Care				Dependency Court			
	Entries	Exits	Volume	Delta	Openings	Closings	Volume	Delta
Mean	9	9	18	0	4	4	7	0
Standard Deviation	5	5	7	6	3	3	5	4
Median	9	8	17	0	3	3	7	0
Mode	9	6	15	-3	3	1	4	2
Minimum	0	0	2	-21	0	0	0	-20
Maximum	27	28	47	16	19	22	30	15

APPENDIX B: QUALITATIVE INTERVIEW QUESTIONS

Question Category	Questions (Out-of-home care)
Sense of population size	Do you have a feel for how many children are in out-of-home care in this county/in the state? Do you have a feel for how many open dependency cases there are in this county? Are there times when you think that there are a whole lot of or not very many kids in out-of-home care? Are there times when you think that there are a whole lot of or not very many open dependency cases?
Sense of rate of change	Do you have a feel for whether a lot of children are being placed in out-of-home care during a given time? Do you have a feel for whether a lot of dependency cases are being opened during a given time?
Information flow	How do you know that a during a particular time there are a whole lot or not very many kids in out-of-home care/open dependency cases? How do you know that during a particular time there are lots of children entering or leaving out-of-home care or cases opening or closing? Do you regularly talk with child welfare workers or lawyers about how many children are in out-of-home care or how many open cases there are in dependency court?
Difference in practice	Do you feel like the number of children in out-of-home care effects how easy or hard it is to place a child in out-of-home care? Do you feel like the number of children in out-of-home care effects how easy or hard it is to open a new judicial case? Do you feel like the number of children in out-of-home care effects how busy the courts are? Do you feel like the number of children in out-of-home care effects how difficult it is to get a hearing? Do you feel like the number of children in out-of-home care effects how long cases take? Do you feel like the number of children in out-of-home care effects how easy or hard it is to close a judicial case? Do you feel like the number of children in out-of-home care effects how easy or hard it is to exit a child from out-of-home care? Do you feel like the number of children in out-of-home care effects how easy or hard it is to communicate with caseworkers? Do you feel like the number of children in out-of-home care effects how easy or hard it is to communicate with judges or lawyers? Do you feel like the number of children with open dependency cases effects how easy or hard it is to place a child in out-of-home care? Do you feel like the number of children with open dependency cases effects how easy or hard it is to open a new judicial case? Do you feel like the number of children with open dependency cases effects how busy the courts are? Do you feel like the number of children with open dependency cases effects how difficult it is to get a hearing? Do you feel like the number of children with open dependency cases effects how long cases take? Do you feel like the number of children with open dependency cases effects how easy or hard it is to close a judicial case? Do you feel like the number of children with open dependency cases effects how easy or hard it is to exit a child from out-of-home care? Do you feel like the number of children with open dependency cases effects how easy or hard it is to communicate with caseworkers? Do you feel like the number of children with open dependency cases effects how easy or hard it is to communicate with judges or lawyers?

APPENDIX C: SIMPLEX COEFFICIENTS BY COUNTY

Values are reported as simplex coefficients. All values are statistically significantly different than zero ($P \leq 0.05$) unless otherwise indicated by italics and a light grey box. Null reports represent a value, assumed to be zero, not capable of being determined by the test.

County	Variable	Simplex Rho	Variable	Simplex Rho
Clark	FC entry	0.1244	Fdelta	*null*
	FC exit	0.1654	Fvol	0.2772
	Court entry	0.1216	Cdelta	*null*
	Court exit	0.0952	Cvol	0.1134
King	FC entry	0.2545	Fdelta	0.1198
	FC exit	0.2450	Fvol	0.3243
	Court entry	0.1470	Cdelta	*null*
	Court exit	0.0910	Cvol	0.1313
Pierce	FC entry	0.1742	Fdelta	*null*
	FC exit	0.0736	Fvol	0.2029
	Court entry	0.3294	Cdelta	*null*
	Court exit	0.2195	Cvol	0.3381
Snohomish	FC entry	*null*	Fdelta	0.0709
	FC exit	0.1236	Fvol	0.1107
	Court entry	*null*	Cdelta	0.1014
	Court exit	0.1372	Cvol	*null*
Spokane	FC entry	*null*	Fdelta	*null*
	FC exit	0.0711	Fvol	*0.0418*
	Court entry	0.2619	Cdelta	0.0712
	Court exit	0.3155	Cvol	0.4173

Yakima

FC entry	0.1729
FC exit	0.2027
Court entry	*null*
Court exit	*0.0497*

Fdelta	*null*
Fvol	0.3355
Cdelta	*null*
Cvol	0.0603

APPENDIX D: CORRELATION MATRIX BY COUNTY

Values are reported as Pearson correlation coefficients. Lag lengths are reported parenthetically next to the variable by which the lag was set.

Clark

	FE (l7)	FR (l8)	Fdelta (l6)	Fvol (l1)	CF (l6)	CD (l8)	Cdelta (l6)	Cvol (l6)
FE	0.1538	0.1096	0.0587	0.227	0.0754	0.0768	0.0790	0.0321
FR	0.0937	0.1778	-0.0279	0.1819	0.0576	0.1018	0.0059	0.0748
Fdelta	0.0506	-0.0579	0.0733	0.0381	0.0149	-0.0213	0.0618	-0.0363
Fvol	0.1532	0.1779	0.019	0.2531	0.0823	0.1106	0.0525	0.0662
CF	0.0689	0.0078	0.0430	0.0605	0.1712	0.1200	0.0983	0.1479
CD	0.0332	0.0807	0.0499	0.0163	0.0765	0.1319	-0.0342	0.1384
Cdelta	0.028	-0.0521	-0.0035	0.0339	0.0738	-0.0045	0.0986	0.0118
Cvol	0.0701	0.0591	0.00632	0.0530	0.1702	0.1716	0.0457	0.1951

King

	FE (l7)	FR (l1)	Fdelta (l1)	Fvol (l1)	CF (l6)	CD (l1)	Cdelta (l3)	Cvol (l6)
FE	0.1708	0.1628	0.0068	0.2176	0.049	-0.0432	0.0219	0.0469
FR	0.0926	0.2357	-0.1621	0.1819	-0.0454	0.0857	-0.1215	0.0023
Fdelta	0.0577	-0.0700	0.1420	0.0185	0.0768	-0.1064	0.1198	0.0351
Fvol	0.1650	0.2533	-0.1016	0.2518	0.0004	0.0295	-0.0659	0.0302
CF	0.0452	-0.0247	0.0687	0.0209	0.1719	-0.0164	0.0972	0.1562
CD	0.0394	0.0343	0.0047	0.0484	0.0702	0.0906	-0.0660	0.0786
Cdelta	0.0034	-0.0427	0.0454	-0.0206	0.0707	-0.0780	0.1174	0.0534
Cvol	0.0588	0.0073	0.503	0.0484	0.1671	0.0000	0.0199	0.1623

Pierce

	FE (l1)	FR (l4)	Fdelta (l4)	Fvol (l1)	CF (l1)	CD (l4)	Cdelta (l2)	Cvol (l4)
FE	0.2489	0.1204	0.0056	0.3070	0.2247	-0.0568	0.1783	-0.0036
FR	-0.0215	0.1122	-0.0878	0.0164	-0.0815	0.0890	0.0123	0.0418
Fdelta	0.2042	0.0023	0.0734	0.2179	0.2335	-0.1128	0.1243	-0.0356
Fvol	0.1449	0.1528	-0.0554	0.2076	0.0891	0.0234	0.1226	0.0258
CF	0.1516	0.0303	0.0229	0.1282	0.3507	0.1311	0.1484	0.2534
CD	-0.1026	-0.0080	-0.0684	-0.0713	0.0711	0.2056	-0.0393	0.2327
Cdelta	0.1889	0.02777	0.0706	0.1474	0.1908	-0.0714	0.1361	-0.0069
Cvol	0.0222	0.0133	-0.0341	0.0297	0.2699	0.2279	0.0650	0.3237

Snohomish

	FE (l7)	FR (l1)	Fdelta (l1)	Fvol (l6)	CF (l7)	CD (l2)	Cdelta (l6)	Cvol (l7)
FE	0.0252	0.0235	-0.0029	0.0982	0.0749	-0.0206	0.0353	0.0813
FR	0.0152	0.1415	-0.1623	0.0519	-0.0361	0.1807	-0.0473	0.1109
Fdelta	0.0048	-0.0939	0.1235	0.0243	0.0772	-0.1532	0.0597	-0.0324
Fvol	0.0274	0.1216	-0.1240	0.1017	0.0208	0.1227	-0.0131	0.1351
CF	0.0271	-0.0252	0.0137	0.0374	0.0628	-0.0370	0.0713	0.1004
CD	-0.0305	0.1160	-0.0949	0.0751	-0.0100	0.1480	-0.1386	0.0790
Cdelta	0.0413	-0.1059	0.0820	-0.0332	0.0492	-0.1383	0.1539	0.0054
Cvol	-0.0054	0.0708	-0.0624	0.0801	0.0328	0.0872	-0.0580	0.1236

Spokane

	FE (l8)	FR (l4)	Fdelta (l7)	Fvol (l6)	CF (l2)	CD (l5)	Cdelta (l3)	Cvol (l5)
FE	0.0905	0.0531	0.0006	0.1044	0.0178	-0.0061	0.0778	-0.0052
FR	-0.0222	0.0855	0.0126	0.0490	-0.0002	0.0693	-0.0970	0.0192
Fdelta	0.0824	-0.0260	-0.0090	0.0384	0.0131	-0.0565	0.1291	-0.0182
Fvol	0.0450	0.0948	0.0091	0.1036	0.0117	0.0441	-0.0155	0.0099
CF	0.0191	0.0273	0.0067	0.0158	0.2272	0.1778	0.0221	0.2374
CD	-0.0821	0.0281	-0.0245	-0.0502	0.1761	0.2693	-0.1119	0.02891
Cdelta	0.0789	-0.0016	0.0243	0.0513	0.0319	-0.0781	0.1047	-0.0490
Cvol	-0.0430	0.0364	-0.0122	-0.0236	0.2644	0.2959	-0.0611	0.3476

Yakima

	FE (l6)	FR (l1)	Fdelta (l6)	Fvol (l2)	CF (l7)	CD (l1)	Cdelta (l8)	Cvol (l7)
FE	0.2227	0.2585	0.0894	0.2483	-0.0228	-0.0237	0.0060	0.0082
FR	0.1525	0.1513	0.0216	0.1585	-0.0230	0.0244	-0.0911	-0.0275
Fdelta	0.0678	0.0996	0.0596	0.0848	-0.0009	-0.0405	0.0795	0.0295
Fvol	0.2345	0.2565	0.0702	0.2544	-0.0285	-0.0004	-0.0512	-0.0133
CF	-0.0332	0.0399	-0.0194	-0.0357	0.0318	0.0385	-0.0310	0.1199
CD	0.0461	-0.0594	0.0709	-0.0221	0.0267	-0.0312	0.0331	0.0380
Cdelta	-0.0576	0.0721	-0.0667	-0.0081	0.0020	0.0500	-0.0462	0.0546
Cvol	0.0133	-0.0164	0.0384	-0.0397	0.0404	0.0031	0.0032	0.1071

APPENDIX E: CONVERGENT CROSS MAPPING MATRIX BY COUNTY

Values are reported as CCM coefficients. Outcome variables are listed along the top, with predictors listed to the left. Embedding dimensions and lag lengths are reported parenthetically next to the outcome variable. All values are statistically significantly different than zero ($P \leq 0.05$) unless otherwise indicated by italics and a light grey box. Null reports represent a value, assumed to be zero, not capable of being determined by the test.

Clark

	FE (l7, e3)	FR (l8, e3)	Fdelta (l6, e9)	Fvol (l1, e5)	CF (l6, e3)	CD (l8, e4)	Cdelta (l6, e5)	Cvol (l6, e3)
FE		0.1512	0.0587	0.2270	0.2043	*0.0336*	0.0790	0.0321
FR	0.2318		*null*	0.1819	0.0576	0.1018	*0.0059*	0.0748
Fdelta	0.4051	0.4244		0.0381	*0.0149*	*null*	0.0618	*null*
Fvol	0.6793	0.6756	*0.0190*		0.0823	0.1106	0.0525	0.0662
CF	0.2539	*0.0008*	*0.0430*	0.0605		0.1200	0.0983	0.1479
CD	*0.0275*	*0.0349*	*0.0499*	*0.0163*	0.0765		*null*	0.1384
Cdelta	0.1213	*0.0263*	null	*0.0339*	0.0738	*null*		*0.0118*
Cvol	0.1677	*0.0190*	0.0063	0.0530	0.1702	0.1716	*0.0457*	

King

	FE (l7, e9)	FR (l1, e4)	Fdelta (l1, e5)	Fvol (l1, e3)	CF (l6, e9)	CD (l1, e6)	Cdelta (l3, e3)	Cvol (l6, e4)
FE		0.1661	0.5266	0.6132	0.2223	*null*	0.0792	0.0817
FR	0.1037		0.6174	0.6778	*null*	*0.0341*	*0.0223*	*0.0083*
Fdelta	0.4404	0.6388		0.0595	0.1566	0.0547	0.1350	*0.0503*
Fvol	0.6248	0.7617	*0.0098*		0.1260	*0.0001*	*0.0212*	0.1025
CF	0.2468	*null*	0.2365	0.0927		*null*	0.5092	0.5369
CD	0.0226	0.0607	*0.0343*	*0.0390*	*null*		0.5322	0.5497
Cdelta	0.1052	*0.0007*	0.1967	*0.0113*	0.5313	0.7132		0.1429
Cvol	0.0968	*null*	*0.0079*	0.1095	0.5539	0.6718	*0.0171*	

Pierce

	FE (l1, e6)	FR (l4, e7)	Fdelta (l4, e9)	Fvol (l1, e10)	CF (l1, e7)	CD (l4, e6)	Cdelta (l2, e5)	Cvol (l4, e4)
FE		*null*	0.4575	0.7210	0.2259	*0.0407*	0.1258	0.0769
FR	0.0775		0.4973	0.7451	*0.0284*	0.1772	0.0628	0.0809
Fdelta	0.5077	0.5179		0.1581	0.1906	0.1526	0.2099	0.0621
Fvol	0.6173	0.6279	null		0.0723	*0.0138*	*0.0003*	0.1569
CF	0.1946	*null*	0.1574	0.1809		*0.0350*	0.3614	0.5222
CD	*0.0367*	0.2011	0.1548	0.1096	*null*		0.4998	0.6082
Cdelta	0.2060	0.0779	0.2408	0.0853	0.5515	0.6433		0.2314
Cvol	0.1016	0.0896	*0.0040*	0.2208	0.5824	0.6355	0.0575	

Snohomish

	FE (l7, e6)	FR (l1, e5)	Fdelta (l1, e3)	Fvol (l6, e4)	CF (l7, e5)	CD (l2, e5)	Cdelta (l6, e10)	Cvol (l7, e3)
FE		*0.0041*	0.4245	0.6241	0.3660	*null*	0.3222	0.2010
FR	*0.0308*		0.6103	0.7466	*null*	0.1077	*0.0221*	*0.0405*
Fdelta	0.5667	0.6806		0.3757	0.2082	0.0672	0.2304	0.1100
Fvol	0.4739	0.6328	0.0963		0.1699	*0.0372*	0.0595	0.1763
CF	0.4382	*null*	0.1693	0.3366		*0.0359*	0.605	0.4736
CD	*null*	0.0510	*0.0364*	*0.0395*	*0.0262*		0.7311	0.6018
Cdelta	0.1800	0.0504	0.1343	0.1119	0.4853	0.6182		0.2099
Cvol	0.2282	0.0302	*0.0442*	0.2865	0.4796	0.0564	0.0805	

Spokane

	FE (l8, e6)	FR (l4, e5)	Fdelta (l7, e3)	Fvol (l6, e3)	CF (l2, e4)	CD (l5, e5)	Cdelta (l3, e10)	Cvol (l5, e6)
FE		0.0136	0.4575	0.5456	0.2277	*null*	0.2651	0.0814
FR	null		0.4973	0.5890	*null*	null	0.0522	*null*
Fdelta	0.5274	0.4928		0.0542	0.1702	0.0454	0.2879	0.0763
Fvol	0.6011	0.5820	*null*		0.0737	null	*null*	0.1116
CF	0.2654	0.0008	0.1574	0.0990		0.0700	0.5947	0.6532
CD	0.0580	0.0696	0.1548	0.0535	0.0865		0.6271	0.6803
Cdelta	0.1855	0.0117	0.2408	*0.0293*	0.4682	0.4945		0.0871
Cvol	0.1880	0.0170	*0.0040*	0.0812	0.5923	0.6003	*0.0129*	

Yakima

	FE (l6, e8)	FR (l1, e5)	Fdelta (l6, e8)	Fvol (l2, e6)	CF (l7, e6)	CD (l1, e6)	Cdelta (l8, e10)	Cvol (l7, e4)
FE		null	0.4715	0.8033	0.0587	*0.0216*	*0.0373*	*0.0182*
FR	0.1667		0.3958	0.7817	*null*	0.0775	*0.0331*	0.0774
Fdelta	0.5153	0.4369		0.2579	*null*	*0.0199*	0.0593	*0.0113*
Fvol	0.6640	0.6633	*null*		*0.0434*	*0.0210*	0.0518	0.0984
CF	0.0754	null	*0.0247*	0.0707		*0.0261*	0.5437	0.4737
CD	0.0093	0.0548	0.0529	0.0605	*null*		0.6272	0.5592
Cdelta	0.0501	0.0047	0.0760	*0.0388*	0.6293	0.7255		0.2859
Cvol	0.1507	null	0.0556	0.0862	0.5329	0.6028	*0.0132*	