DISSERTATION

THE PHYSIOLOGICAL CONDITION OF ORPHANED AFRICAN ELEPHANTS

(*LOXODONTA AFRICANA*)

Submitted by

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ABSTRACT

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Prolonged maternal care is an energetically expensive behavior, yet it has evolved in many mammal species. This is presumably because of its benefits to offspring even after they are weaned, including defense again aggression from other individuals of the same species, protection from predation, provisioning of food, transfer of knowledge, and inherited rank for offspring of high-ranking individuals. We know these benefits matter because studies have shown that weaned orphans of some long-lived mammal species survive less than weaned nonorphans. However, we lack understanding of the physiological mechanisms leading to lowered survival for weaned orphans who are no longer dependent on their mother's milk. Understanding physiological benefits of prolonged maternal care is valuable to understanding how it evolved, and, as some have speculated prolonged parental care was a cornerstone in the evolution of sociality, to further understanding sociality. Moreover, many long-lived species for which prolonged maternal care is fundamental are also of conservation concern, some due to practices like poaching that kill adults and leave orphans behind. Yet we were previously unaware of how orphan deaths impact population growth.

African elephants (*Loxodonta africana*) are a highly social species, and the mother-calf bond is exceptionally important to elephant society. They are also endangered due to habitat loss and poaching, the latter of which removes adults from populations for their ivory tusks. My colleagues and I investigated the physiological consequences of losing prolonged maternal care

by comparing the physiology and survival of individually known, wild African elephant orphans with those of their nonorphan peers in the Samburu and Buffalo Springs National Reserves of Kenya. We longitudinally collected dung samples to compare strongylid (gastrointestinal worm) fecal egg counts as a proxy for parasite loads and fecal glucocorticoid concentrations as a proxy for general stress. We also used 19 years of long-term demographic data to compare survival and the effect of orphaning on population growth.

Chapter 1 reveals that we did not discover differences in strongylid infection between orphans and nonorphans, and surprisingly found evidence of *lower* strongylid infection in nonorphans who had left their natal family as compared to natal orphans and nonorphans. This may be due to social isolation; orphans who have left their family receive more aggression and are kept on the periphery of popular social hubs that contain old dung infected with strongylid larvae. In support of this idea, elephants who received more aggression as measured by behavioral focal follows had fewer strongylid eggs in their dung. Further supporting the role of social behavior in determining strongylid infection of wild elephants, we counted more strongylid eggs in the dung samples of females, who are more often in the company of family groups, than males, who spend less time in the company of family groups and more time in areas less contaminated by old dung. Agreeing with findings in other species, younger elephants were more infected with strongylids than older elephants, likely because their immune systems are still developing. Finally, using GPS radio collar data, we determined that elephants spending more time within reserves have fewer strongylid eggs in their dung compared to elephants who spend less time in reserves. This could indicate that livestock grazing outside of reserves is altering soil content so it is more conducive to strongylid larval survival.

Chapter 2 concerns orphan versus nonorphan survival and the effect of orphaning on population growth. We found that even weaned African elephant orphans survive less than their nonorphan peers. Moreover, with a robust sensitivity analysis based on long-term data, we discovered that orphaning substantively decreases population growth. This demonstrates that, on top of its direct effects, adult elephant death indirectly decreases population growth through orphaning. As environmental conditions can affect sensitivity, we reran our analysis twice more using only data from years when there was less poaching in the study system, then only data from years of more poaching. Population growth rate's sensitivity to orphan survival increased for the analysis parameterized with data from years of more poaching, indicating orphan survival is more important for population growth as orphaning increases. We concluded orphaning should not be overlooked when quantifying the impacts of poaching, and population models characterizing systems with extensive parental care benefit from explicitly incorporating orphan stages.

Finally, Chapter 3 provides foundational insight into orphaning's impact on the stress response of a wild long-lived mammal. We found no difference in baseline glucocorticoid levels of orphan and nonorphan elephants two or more years after their mother's death. We did, however, find *lower* average levels in orphans who had left their natal family versus nonorphans and natal orphans. We also found lower glucocorticoid levels in individuals with more adult females and age mates in their core group. The observed lower levels in non-natal orphans were contrary to our predictions and may indicate downregulated glucocorticoid secretion following a period of sustained stress without familial support, which could be adaptive and/or negatively impact fitness. We do not think the lower glucocorticoids in non-natal orphans relate to their lower strongylid infection described in the first chapter, as strongylid egg counts did not correlate with glucocorticoids. Our third chapter findings indicate resilience in surviving orphans who remain with their family following their mother's death, which is hopeful for the recovery of elephant populations that have been moderately poached. Although social context influenced glucocorticoid levels, they correlated most with ecological conditions. Elephants had lower levels when resources were plentiful, and higher levels during seasonal changes when resources were unevenly distributed. We therefore highlight that social context, and most of all ecological conditions, impact the stress response of wild African elephants.

My dissertation indicates that maternal care is important not only to individual survival, but also to larger population dynamics. Therefore, orphaning matters for conserving African elephants and potentially other species with prolonged maternal care. Yet our findings are hopeful for orphans who manage to survive, as only elephant orphans without family showed altered physiology as compared to nonorphans. Concerning parasites, the changes we observed in non-natal orphans were advantageous because they were less infected with strongylids. Regarding the stress response, we found lower glucocorticoid levels in non-natal orphans without the support of family, which could affect their fitness and encourages similar research in heavily poached populations with more non-natal orphans. Broadly, my dissertation reveals that social behavior and social context affect the physiology of orphans, and that prolonged maternal care affects population growth.

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DEDICATION

For my parents, Sheldon and Michelle Parker

because you encouraged me to follow my dreams and always believed in me.

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CHAPTER 1: Strongylid infection varies with age, sex, movement and social factors in wild African elephants[1]

Introduction

Gastrointestinal (GI) nematodes are parasitic worms which infect the intestinal tract of vertebrates (Albery *et al.*, 2018). Although they are known to suppress their host's immune system (Maizels *et al.*, 2012), impede growth (Crompton and Nesheim, 2002), and can decrease reproductive output (Akinyi *et al.*, 2019), they often live many years within a host and generally do not cause mortality (Albery *et al.*, 2018). Nonetheless, mortality has been attributed to GI nematodes in cases of severe infection (Lynsdale *et al.*, 2017; Pihl *et al.*, 2018), and partially attributed to nematodes in cases where individuals were otherwise compromised by poor nutrition or disease (Condy, 1974; Obanda *et al.*, 2011). As such, GI nematodes can affect an individual's fitness.

Studies conducted on wildlife populations have shown that many factors influence how heavily an individual host is infected with GI nematodes, including individual characteristics and environmental factors (e.g. Albery *et al.*, 2018). The individual characteristics of age (Albery *et al.*, 2018), body condition (Sánchez *et al.*, 2018), reproductive status (Cizauskas *et al.*, 2015) and sex (Zuk and McKean, 1996) have been found to influence the susceptibility of a host to infection. For example, young and old hosts tend to be more susceptible than middle-aged adult hosts, likely because the immune systems of young animals are still developing, while the immune systems of old animals are senescing (Albery *et al.*, 2018). Additionally, environmental

[1] Adapted from: Parker, J.M., Goldenberg, S.Z., Letitiya, D., and Wittemyer, G. 2020. Strongylid infection varies with age, sex, movement and social factors in wild African elephants. *Parasitology* 147(3): 348 - 359. doi:10.1017/ S0031182019001653

factors influence the exposure of a host to infection (González-Hernández *et al.*, 2014). These factors include seasonality (Cizauskas *et al.*, 2015), the cleanliness of available water sources (Khan *et al.*, 2010), diet (Leung and Koprivnikar, 2019), and properties of soil such as particle size (Condy, 1974).

Factors affecting exposure can also be social; in fact, parasitism has long been recognized as a cost of social living (Rimbach *et al.*, 2015). There is some evidence that infection with GI nematodes increases with increasing group size (e.g. Ezenwa and Worsley-Tonks, 2018). Studies have also suggested that more dominant individuals (Smyth and Drea, 2015), individuals more centrally located within a social network (MacIntosh *et al.*, 2012), or individuals with social ties to many different social "cliques" (Vanderwaal *et al.*, 2016) may be more exposed to nematode infection, and it has been determined with behavioral focal follows that primates who more frequently touch conspecifics have more GI nematodes (González-Hernández *et al.*, 2014; Rimbach *et al.*, 2015).

Our objective was to determine which of a suite of individual characteristics, environmental factors, and social factors best explained GI nematode loads in a population of individually known African elephants (*Loxodonta africana*). To meet this objective, we approximated infection of elephants with commonly occurring nematodes of the suborder Strongylida. Members of Strongylida known to infect African elephants include *Murshidia* spp., *Quilonia* spp., and *Khalilia* spp. of the Strongylidae family, and *Grammocephalus clathratus* of the Ancylostomatidae family (Allen *et al.*, 1974; Condy, 1974; Mclean *et al.*, 2012). Larvae of these strongylids hatch from eggs in elephant dung, and become infective after a developmental period of several weeks (Condy, 1974; Khan *et al.*, 2015). Then the infective larvae migrate to surrounding soil, the base of plants, and especially to nearby water, where they can be ingested by elephants who are feeding or drinking (Condy, 1974). Once ingested, adults of Strongylidae spp. embed themselves in the intestines, and *Grammocephalus clathratus* in the bile ducts (Condy, 1974). There they lay eggs that are excreted in dung, restarting the life cycle (Condy, 1974; Khan *et al.*, 2015). Strongylid eggs, although difficult to visually distinguish beyond suborder, are easily recognizable under a microscope (Condy, 1974; Thurber *et al.*, 2011). We counted strongylid eggs in dung collected from individuals under a repeated measures sampling design. We tested these counts for correlations with the individual characteristics of age, body condition, reproductive status, and sex; the environmental factors of space use relative to water and protected areas, and seasonality; and the social factors of group size, whether a mother's level of infection might affect that of her calf, physical contact rates, level of social integration, and social network position (Table 1.1). We further explored whether social factors related to disruption might correlate with strongylid egg counts by comparing orphaned elephants to non-orphans, orphans who have left their natal family to orphans who have remained, and orphans whose mother died from drought to orphans whose mother was killed by humans (Table 1.1). This study is the first to investigate such a diverse array of factors in relation to parasitic infection in wild African elephants, and we discuss the conservation implications of our results.

Methods

Study site

We conducted our study within the unfenced Samburu and Buffalo Springs Reserves of Kenya, at 0.3-0.8°N and 37-38°E (Wittemyer *et al.*, 2013). The reserves are separated by a semi-permanent river called the Ewaso Ngiro, and together they encompass 220 km^2 (Wittemyer *et al.*, 2013). Rainfall averages 350 mm per year, falling in the wet seasons that normally occur from

Table 1.1: Factors tested for a correlation with strongylid loads in African elephants

Individual Characteristics	Environmental Factors	Social Factors	
-Age (to date) -Body condition -Reproductive status -Sex	Space use: -Fraction of time spent within 1 km of rivers -Fraction of time spent within versus outside of reserves -Seasonality (measured with NDVI)	-Group size -Mother's strongylid load -Physical contact rate (approximated by focal follows) Social integration (approximated by focal follows): -Rate of affiliative interactions -Received aggression rate Social network metrics: -Betweenness -Degree -Strength	Related to disruption: -Orphan status -With natal family? ("origin") For orphans: -Cause of mother's death

April – May and November – December (Wittemyer *et al.*, 2013). Other months of the year tend to be hot and dry (Wittemyer, 2001).

The elephant population that uses the Samburu and Buffalo Springs Reserves has been studied since 1998, such that detailed demographic and social information is available for approximately 1000 individually known elephants (Wittemyer *et al.*, 2013). This information includes familial relations, reproductive status, precise age estimates to within a few weeks of birth for individuals born during the study period, and information on mortality, with carcass surveys revealing the cause of death in some cases (Wittemyer *et al.*, 2013). Of relevance to this study, these data also provide information on the orphan status of individuals, where orphans were defined as individuals that lost their mother prior to being reproductively mature. Long-term GPS tracking data have shown that the reserves encompass less than 10% of the area used by the study elephants (Wittemyer *et al.*, 2005a), although several well-known families that were the focus of this study spend the majority of their time within reserve boundaries (Goldenberg *et al.*, 2018).

Study subjects

From May 29th of 2015 through July 2nd of 2016, we collected dung samples with a minimum interval of two weeks between samples from a single individual, from 38 weaned orphan (n = 25) and non-orphan (n = 13) female subjects, ranging in age from 7 – 21 years, that are regularly seen during long-term monitoring of the population. Twenty-two of these focal individuals were reproductively active by the time we began sampling, so each female was assigned into one of five categories based on her reproductive condition, with 0 = reproductively inactive, 1 = pregnant, 2 = lactating, 3 = lactating and pregnant with a second calf, and 4 = multiparous (only one female fell into the multiparous category for a part of the study). Of the 25 orphan subjects, 19 remained with their natal family, while 6 stayed with a different family. The cause of death, whether natural or anthropogenic, was known for the mothers of 12 orphan subjects.

We also opportunistically collected samples from the offspring of focal individuals with calves. This was to test for a correlation between mother and calf strongylid loads, and to increase the age range of sampled individuals. We resulted with additional samples from female calves aged 0 – 5 (n = 6), and male calves aged 0 – 3 (n = 9). Further, we opportunistically collected from young bulls to assess sex differences, resulting in additional samples from young bulls aged 8 – 16 (n = 22). In total, we collected 578 samples from 75 individuals.

Fecal sampling and strongylid egg counts

Focal individuals were followed until they produced a dung sample. From these samples, pinches from the center of several dung boli were collected and placed into plastic sealable bags without preservatives as recommended by Lynsdale *et al.* (2015). Eggs are evenly distributed throughout dung boli (Lynsdale *et al.*, 2015), therefore homogenization was unnecessary. We recorded whether adult worms were visible in the dung, because if adult egg layers were being shed, egg counts might be less representative of infection. We did not have the capacity to genotype and identify adult worms, but their appearance was consistent with descriptions of adults of the family Strongylidae (Condy, 1974). We also recorded whether dung was watery, because wateriness might lower egg counts by diluting dung matter.

Sample collection was paired with data records taken at the time the sample was produced, including: number of individuals in the subject's group, date, GPS coordinates, time between sample deposition and collection, and time of day the sample was collected. Further, we assessed body condition of sampled individuals at each collection event, adapting the method of Wijeyamohan *et al.* (2014) based on degree of thinness (i.e. boniness) to African elephants.

One of us (JP) performed fecal egg counts on all samples within 24 hours of returning to camp using the McMaster slide method, exactly as described in Gibbons *et al.* (2004). McMaster slides feature overlaying grids under which floating eggs can be counted to derive an eggs per gram (EPG) measure for each dung sample (Gibbons *et al.*, 2004). This method has been validated as a reasonable estimation of strongylid infection for a subject at the time of sample collection (Seivwright *et al.*, 2004; Levecke *et al.*, 2011). The detection limit of Gibbons *et al.* (2004) is 50 EPG, meaning that if an elephant shed fewer than 50 EPG in their dung, their egg count would likely be zero even though they had some strongylids (Lester and Matthews, 2014). Initially, we used a two-chamber opaque grid McMaster slide (Chalex LLC) prior to switching to a two-chamber green grid McMaster slide (Chalex LLC) because the green grids were easier to see.

Space use

We analyzed GPS points from the collars of 8 tracked females over the study period. The 8 collared females included 4 orphan focal individuals and 4 non-orphan older adult females. The data from their collars accounted for the movements of 17 focal individuals because 4 of them were directly collared, and 13 uncollared focal individuals travelled consistently with a collared individual as part of the same core family (Wittemyer *et al.*, 2005b). Collars reported a GPS location every hour. We analyzed space use data from 7 December 2015 through 10 May 2016, a period during which all collars were reporting that overlapped with the period during which we collected dung. Two metrics were derived for use in analyses: 1) time spent within 1 km of permanent rivers, and 2) time spent within versus outside of reserves. We used ArcGIS version 10.5.1 (ESRI, 2017) to select points within a 1 km buffer of permanent rivers or within the reserves, and derived the proportion of time tracked spent there for each collared elephant.

Physical contact and social integration

One of us (SG) collected focal follow interaction data on a subsample of focal orphan and non-orphan subjects as described in Goldenberg and Wittemyer (2018). Behavioral interactions recorded included affiliative and aggressive behaviors, many of which involved physical contact (Table 1.2). Including only individuals who were observed for 2 or more hours (range 2.18 to 11.85 hours, mean 7.75 hours) while feeding (n = 23), we calculated three per hour rates: a physical contact rate, an affiliation rate, and a received aggression rate (Table 1.2). The latter two rates served as proxies for social integration, because individuals who engage in more affiliative interactions and do not frequently receive aggression tend to be more socially integrated (Goldenberg and Wittemyer, 2018).

Seasonality

As a measure of seasonality, we calculated the normalized difference vegetation index (NDVI), a measure of primary productivity (Prince and Goward, 1995), for a core range area drawn from elephant GPS collar data (Wittemyer *et al.*, 2007). Landsat raster images (Landsat-7 and Landsat-8 images, courtesy of the U.S. Geological Survey) that overlay the core range were extracted from Google Earth Engine (Gorelick *et al.*, 2017) for all dates the satellites passed over during the study period with $\leq$ 70% cloud cover. These rasters were then clipped and processed in R using the raster (Hijmans, 2019), rgdal (Bivand *et al.*, 2019), maptools (Bivand and Lewin-Koh, 2019), sp (Pebesma and Bivand, 2005; Bivand *et al.*, 2013), and reshape2 (Wickham, 2007) packages to obtain NDVI values for the study period.

Social network position

Including only observations for which observers had seen and identified all elephants present, and including only sampled individuals observed 10 or more times during the study period, we

Table 1.2: Ethogram of elephant behaviors recorded during focal follows, and the calculated rates which included each behavior, adapted from Goldenberg and Wittemyer (2018) and Goldenberg (2016)

Interaction	Description	Rates involving the interaction
alloparental	focal protects/comforts a calf that is not her own (associated with calf crying or environmental stimulus)	affiliation, physical contact
allosuckling	calf attempts to breastfeed from focal	affiliation, physical contact
body rub	focal rubs another elephant with her body, or another elephant rubs focal with their body	affiliation, physical contact
displacement	another elephant approaches focal, focal leaves	received aggression
ear brush	focal brushes her ear on another elephant, or another elephant brushes her ear on focal	affiliation, physical contact
forward trunk swing / swat	another elephant swings trunk in direction of focal	received aggression
greeting	focal rumbles when meeting another elephant, or another elephant rumbles when meeting focal	affiliation
head rub	focal rubs another elephant with head, or another elephant rubs focal with head	affiliation, physical contact
herd	focal rubs another elephant or another elephant rubs focal, resulting in their coordinated movement	affiliation, physical contact
kick back	another elephant kicks focal with their back foot	received aggression, physical contact
playful fight	focal and another elephant intertwine heads and spar with no escalation	affiliation, physical contact
playful head rest	focal rests head on another elephant's body, or another elephant rests head on focal's body	affiliation, physical contact
pursuit	another elephant chases focal	received aggression
push	another elephant pushes focal	received aggression, physical contact
smells genitalia	focal reaches trunk to smell another elephant's genetalia, or another elephant reaches trunk to smell focal's genetalia	affiliation, physical contact
stand tall	another elephant faces focal with head held above shoulders	received aggression
supplant	another elephant approaches focal, and takes focal's place	received aggression

test mouth	focal holds trunk to another elephant’s mouth, or another elephant holds trunk to focal’s mouth	affiliation, physical contact
trunk grasp	focal grabs another elephant’s trunk, or another elephant grabs focal’s trunk	affiliation, physical contact
trunk touch	focal touches another elephant with turnk, or another elephant touches focal with trunk	affiliation, physical contact
tusk	another elephant hits/pokes focal with tusks	received aggression, physical contact
tusk rub	focal rubs another elephant with tusk, or another elephant rubs focal with tusk	affiliation, physical contact

calculated simple ratio indices from association data as measures of bond strength (Ginsberg and Young, 1992). These association data were recorded based on the proximity of elephants to one another (Wittemyer *et al.*, 2005b). Elephants generally cluster such that it is easy to distinguish socially interacting groups, but if there was any doubt, we considered those elephants that were within an estimated 500 m radius of a group's center to be together (Wittemyer *et al.*, 2005b). We used bond strengths to construct social networks and calculated the social network metrics of betweenness, degree and strength (Barrat *et al.*, 2004; Krause *et al.*, 2007) with the packages statnet (Hunter *et al.*, 2008; Handcock *et al.*, 2018) and igraph (Csárdi and Nepusz, 2006) in R. These metrics were chosen because they measure varying aspects of how socially connected an elephant is within their society that could influence strongylid infection (Krause *et al.*, 2007; Farine and Whitehead, 2015). Degree offers a coarse measure of gregariousness because it is the total number of other individuals with which an individual has been in close proximity (Krause *et al.*, 2007; Farine and Whitehead, 2015). Betweenness measures an individual's role in population interconnectedness by quantifying how often they are the shortest connection between two other individuals who are not themselves directly connected (Krause *et al.*, 2007; Farine and Whitehead, 2015). Strength measures the sum of associations to others with whom they share connections (Farine and Whitehead, 2015).

Statistical analyses

Analyses were conducted in R using generalized linear mixed effects models with a negative binomial error distribution and Adaptive Gauss-Hermit Quadrature (Kim and Kyung, 2017). Number of EPG was the response variable in all models, with individual set as the random effect, and family set as an additional random effect in models not including bulls. We controlled for the presence or absence of adult worms in dung ("visible worms"), time difference between when a sample was dropped and collected ("time difference"), grid type (engraved/green), whether a sample was watery (a binary variable hereafter referred to as "wateriness") and the number of samples collected per individual ("$n_{per\ subject}$") by including them as fixed effects in all models.

The individual characteristic factors of age and sex, environmental factor of NDVI, and social factor of group size were included as fixed effects in all models, except for analyses involving only females, for which sex was not included. Because focal follow, social context and spatial data were not available for all sampled individuals, reproductive status was only precisely known for females, and elephants were not always visible enough to record a reliable body condition score, the number of samples available to explore the influence of different factors on EPG varied. Therefore, we implemented seven distinct models to assess the full suite of individual, environmental and social factors we were interested in. The models are detailed in Tables 1.3 – 1.5, which depict the variables included and varying sample sizes for each.
We used the MASS (Venables and Ripley, 2002) and lme4 (Bates *et al.*, 2015) packages for all analyses except for the analysis including reproductive condition, which involved a categorical variable with more than two categories; for that we used the glmmADMB package (Fournier *et al.*, 2012; Skaug *et al.*, 2016). All numeric variables were scaled prior to analyses with the scale function in base R, which subtracts mean and divides by standard deviation. To select top models, we used stepwise backward selection, sequentially removing the least important variable as determined by the lowest absolute value of β / SE and continuing if the lower order model had a lower AICc value (Burnham and Anderson, 2004) than the previous model (Pagano and Arnold, 2009; Arnold, 2010). We did this until removing a variable increased the AICc value,

then kept the previous model with the lower AICc value (Pagano and Arnold, 2009; Arnold, 2010).

Results

Strongylid counts were highly variable, even among samples of a single individual, oscillating up and down over time (Supplementary Figure A1). Across all 578 samples, 557 had positive counts, while 21 had a count of zero that signified fewer than 50 EPG. The positive counts averaged 1,694.2 $\pm$ 60.5 EPG, with a maximum of 10,550 EPG and a minimum of 50 EPG. None of the elephants consistently had negative EPG counts, meaning that every sampled individual was positively infected with strongylids at least once over the course of the study.

Individual characteristics

Our top models indicated that age was one of the strongest predictors of strongylid load (Table 1.3, Figure 1.1). Younger individuals had higher loads than adults; Model 1 estimated that an increase of one standard deviation in age corresponded to a decrease of 12.1% in EPG counts ($p = 0.006$; Table 1.3). Sex also showed a significant effect, with males estimated to have 29.6% fewer EPG than females in Model 1 ($p = 0.036$; Table 1.3, Figure 1.2). Body condition and reproductive status were not included in top models (Tables 1.3, 1.5B).

Environmental factors

Space use with respect to the fraction of time elephants spent within versus outside of reserves showed a significant effect in Model 2, where a one standard deviation increase in the time spent within reserves corresponded to an estimated decrease of 37.7% in EPG ($p = 0.016$; Table 1.4, Figure 1.3). Space use with respect to fraction of time spent near rivers and seasonality as measured by NDVI were not included in top models (Tables 1.3 – 1.5).

Table 1.3: Top model after lowest AICc selection for the model created to test individual characteristics including body condition but not reproductive status, because we did not know the reproductive status of all individuals included in Model 1. Theta is the dispersion parameter. One asterisk signifies a p-value < 0.05, two asterisks signify a p-value <0.01, and three asterisks signify a p-value < 0.001. Covariates showing a trend with a p-value < 0.10 are followed by a period.

Model number and covariates in global model	Data	θ	Covariates in top model	Estimate	p-value
1					
intercept (ID)	all individuals	0.914	intercept***	7.817	$< 2 \cdot 10^{-16}$
age					
body condition	$n_{elephants} = 75$		age**	-0.129	0.006
grid type					
group size	$n_{samples} = 560$		grid type***	green -0.489	$2.28 \cdot 10^{-05}$
$n_{per\ subject}$					
NDVI			$n_{per\ subject}$*	-0.136	0.027
sex					
time difference			sex*	male -0.351	0.036
visible worms					
wateriness					

Table 1.4: Top model after lowest AICc selection for the model created to test environmental factors including movement measures. Theta is the dispersion parameter. One asterisk signifies a p-value < 0.05, two asterisks signify a p-value <0.01, and three asterisks signify a p-value < 0.001. Covariates showing a trend with a p-value < 0.10 are followed by a period.

Model number and covariates in global model	Data	θ	Covariates in top model	Estimate	p-value
2					
intercept (ID)	individuals collared with a GPS collar	1.043	intercept***	7.429	$< 2 \cdot 10^{-16}$
age	or traveling with a collared individual				
fraction of time spent within 1 km of rivers			age*	-0.205	0.046
fraction of time spent within versus outside	$n_{elephants}$ = 17 (all female)				
of reserves			fraction of time spent	-0.474	0.016
grid type	$n_{samples}$ = 121		within versus outside		
group size			of reserves*		
$n_{per\ subject}$					
NDVI			$n_{per\ subject}$.	0.343	0.076
origin					
orphan status			time difference***	-0.323	0.000
time difference					
visible worms					
wateriness					

Table 1.5: Top models after lowest AICc selection for the models created to test A) social factors including the EPG count of a calf's mother's eggs (Model 3), physical contact behavior (Model 4) and social network metrics (Model 5) and B) social factors related to disruption including orphan status and origin (Model 6) and cause of mother's death for orphans (Model 7). Note that the individual characteristic of reproductive status is included in Model 6, because we did not know the reproductive status of all individuals included in Model 1 (see Table 1.3). Theta is the dispersion parameter. One asterisk signifies a p-value < 0.05, two asterisks signify a p-value <0.01, and three asterisks signify a p-value < 0.001. Covariates showing a trend with a p-value < 0.10 are followed by a period.

A

Model and covariates in global model	Data	θ	Covariates in top model	Estimate	p-value
3					
intercept (ID)	young calf samples collected on dates	1.109	intercept***	8.371	$< 2 \cdot 10^{-16}$
age	that we also got a sample from the				
grid type	mother		grid type*	green -0.843	0.015
group size					
EPG count of mother's dung sample	$n_{elephants} = 14$		group size.	-0.284	0.053
$n_{per\ subject}$					
NDVI	$n_{samples} = 44$		$n_{per\ subject}$*	0.299	0.043
time difference					
visible worms					
wateriness					
4					
intercept (ID)	focal individuals for which focal	0.853	intercept***	7.496	$< 2 \cdot 10^{-16}$
affiliation rate	follow behavioral data was collected				
age			age.	-0.133	0.051
grid type	$n_{elephants} = 23$ (all female)				
group size			grid type	-0.259	0.131
$n_{per\ subject}$	$n_{samples} = 309$				
NDVI			$n_{per\ subject}$.	-0.120	0.072
origin					
orphan status			received aggression rate.	-0.114	0.067
physical contact rate					
received aggression rate			time difference**	-0.178	0.009
time difference					
visible worms					
wateriness					

5 intercept (ID) age betweenness degree grid type group size $n_{per\ subject}$ NDVI sex strength time difference visible worms wateriness	individuals observed 10 or more times during the study period $n_{elephants} = 70$ $n_{samples} = 566$	0.895	intercept*** age** grid type*** $n_{per\ subject}$. sex.	7.812 -0.139 green -0.491 -0.120 -0.321	$< 2 \cdot 10^{-16}$ 0.003 $< 2.62 \cdot 10^{-5}$ 0.058 0.062
B					
6 intercept (ID) age grid type group size $n_{per\ subject}$ NDVI origin orphan status reproductive status time difference visible worms wateriness	focal individuals $n_{elephants} = 38$ (all female) $n_{samples} = 462$	0.960	intercept*** age* grid type* $n_{per\ subject}$** origin. time difference**	7.255 -0.094 -0.316 -0.149 with family 0.361 -0.141	$< 2 \cdot 10^{-16}$ 0.046 0.012 0.009 0.087 0.006
7 intercept (ID) age cause of mother death grid type group size $n_{per\ subject}$	orphan subjects whose mom died due to a known cause, natural (from drought) or anthropogenic (illegal killing $n_{elephants} = 12$ (all female)	1.291	intercept*** age** cause of mother death	5.907 -0.284 natural 0.261	$< 2 \cdot 10^{-16}$ 0.000 0.121

NDVI origin time difference visible worms wateriness	$n_{samples} = 154$	$n_{per\ subject}$*	-0.188	0.041
		origin.	with family 1.397	0.052
		time difference**	-0.212	0.004
		visible worms**	visible -0.956	0.009

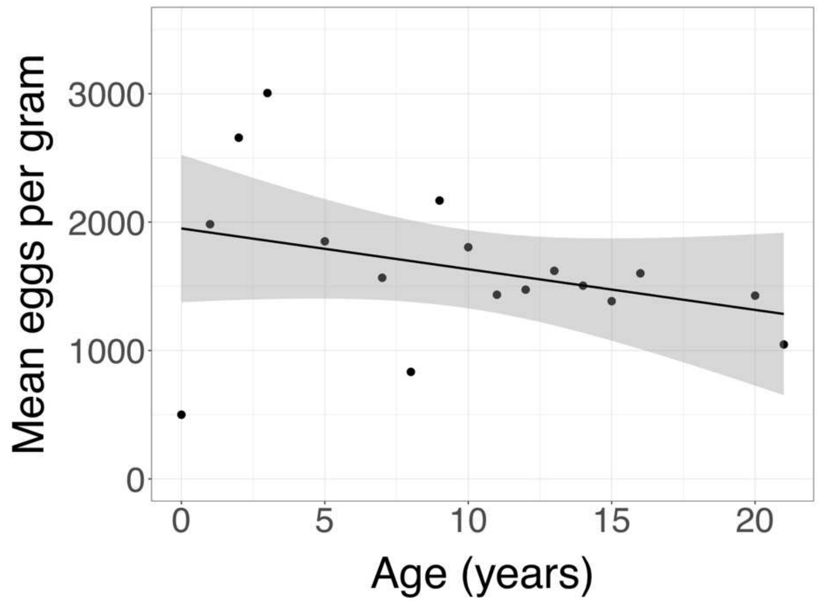


Figure 1.1: Mean strongylid eggs per gram of elephant dung versus elephant age in years

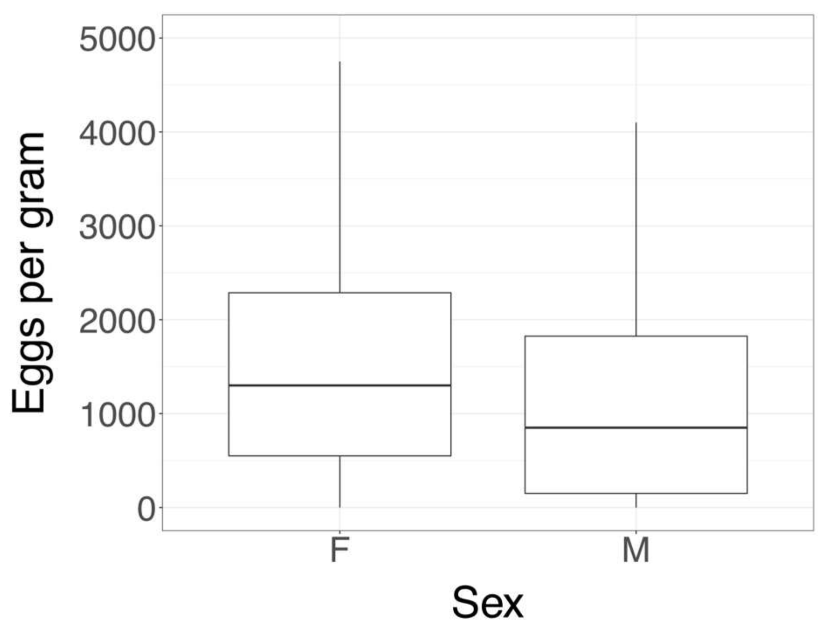


Figure 1.2: Boxplot showing eggs per gram of dung versus sex for elephants 8 years and older. Outliers are not pictured for scale.

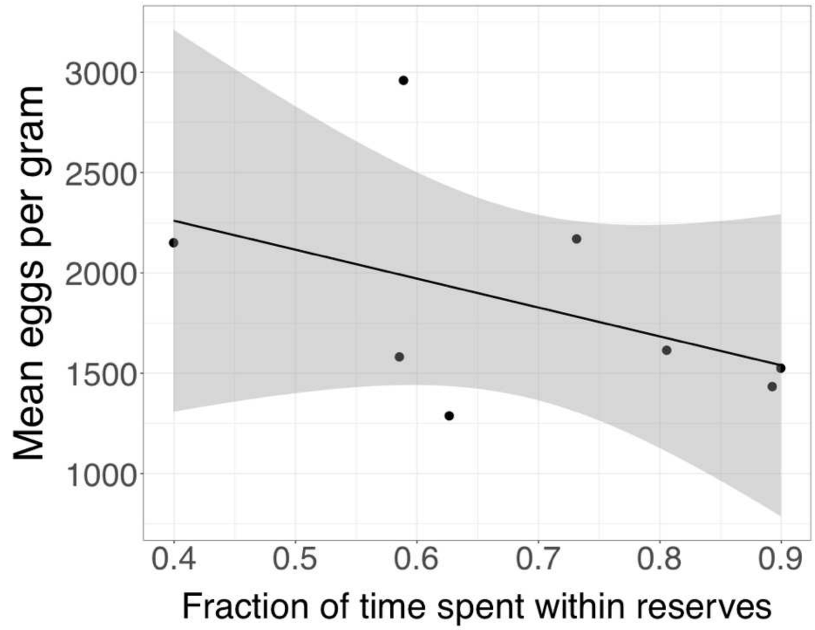


Figure 1.3: Mean eggs per gram of dung versus the time collared individuals spent within reserves

Social factors

Out of the seven top models with different sample sizes, group size appeared only in Model 3, the model including only calves (Table 1.5A). Its estimated effect in that model was nearly significant, with one standard deviation increase in group size corresponding to a decrease of 24.7% in EPG ($p = 0.054$; Table 1.5A). According to the top model, EPG counts of samples collected from mothers were not correlated with counts of samples collected from their calves on the same date (Table 1.5A).

Physical contact rate did not remain in Model 4 following model selection (Table 1.5A). With respect to the two proxies for social integration, affiliation rate did not remain in the top model, but received aggression rate showed a negative trend. Model 4 estimated that one standard deviation increase in the amount of aggression an elephant received per hour correlated with a 10.8% decrease in EPG counts (p = 0.067; Table 1.5A, Figure 1.4). None of the social network metrics of betweenness, degree or strength remained in Model 5 following model selection (Table 1.5A).

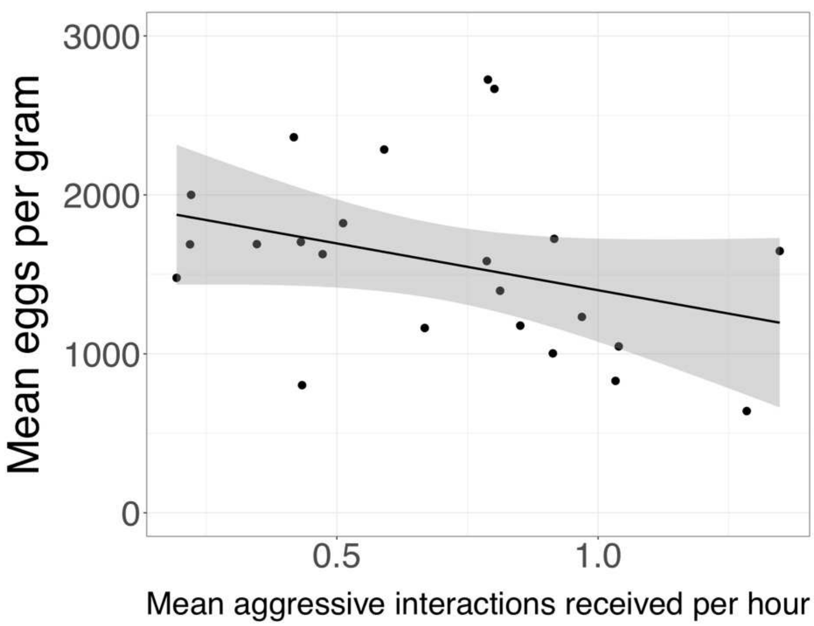


Figure 1.4: Relationship between mean eggs per gram of dung and the rate of aggressive interactions received per hour while feeding

Social factors related to disruption

Orphan status did not appear in any of the top models (Tables 1.4 – 1.5). Origin showed a trend in Models 6 and 7. The estimate of Model 6 is likely more reliable since only one individual included in Model 7 had left her natal family (Table 1.5B); Model 6 estimated that individuals remaining with their natal family had 43.5% higher EPG counts than individuals who had left their natal family (p = 0.087; Table 1.5B, Figure 1.5).

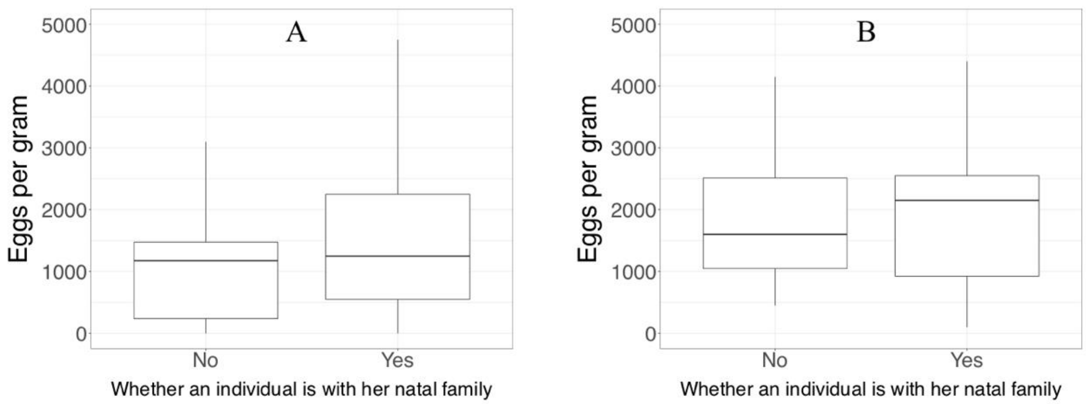


Figure 1.5: Boxplot showing eggs per gram of dung versus origin for female elephant individuals A) $\leq$ 10 years of age and B) > 10 years of age. Due to the effect of age on egg counts, the trend is difficult to see with all ages combined. Outliers are not pictured for scale.

Cause of mother's death remained in Model 7, with orphans of mothers who died due to drought estimated to have 29.8% higher EPG counts than orphans whose mother died due to anthropogenic causes, but the estimated effect was not significant (p = 0.121; Table 1.5B).

Discussion

Studying strongylid infection of individuals in wildlife populations improves our understanding of factors influencing parasitic disease ecology. Our results suggest that multiple factors, representing all three categories of individual characteristics, environmental factors and social factors, play a role in determining the level of strongylid infection in wild African elephants. The individual characteristics of age and sex had robust effects on strongylid loads in this study (Figures 1.1 – 1.2), unsurprising given that previous studies have shown these two factors influence parasitism (e.g. Thurber *et al.*, 2011; Albery *et al.*, 2018). Concerning environmental factors, space use outside of protected areas was positively correlated with strongylid infection. We interpret this result as indicating that human modification of landscapes may alter parasitic infection in wildlife. Other findings concern social factors. We are the first to show that elephants who are frequent recipients of aggressive behaviors have decreased strongylid egg output (Figure 1.4). Correspondingly, orphan elephants who travel with unrelated elephants and are often observed on the periphery of the family group (Goldenberg and Wittemyer, 2018) shed fewer strongylid eggs (Figure 1.5), suggesting that social disruption caused by humans can alter parasitic infection for individuals of social wildlife species.

Key factors determining strongylid infection

Younger elephants had higher strongylid loads (Figure 1.1), a result that is consistent with studies in many species, and may be due to the immature immune systems of younger animals (Albery *et al.*, 2018). Our age results are particularly robust given that age was entered into analyses down to the fraction of a year that had passed since an individual's last birthday for each date dung was collected, whereas other studies of parasitism in elephants relied on coarse age class estimates (e.g. Thurber *et al.*, 2011; Baines *et al.*, 2015). Of note, the oldest sampled female elephant in our study was 21 years old, and the oldest sampled male was 18 years old. Consequently, we do not have insight into strongylid loads in older aged African elephants.

Our results on the influence of sex are consistent with those of Thurber *et al.* (2011), who found that bull elephants have lower strongylid EPG counts than females and calves. However, the sex difference they found was more pronounced, potentially because they sampled from older bulls than those included in our sample (Supplementary Figure A2). Males go through a gradual dispersal process, beginning anywhere from 5 – 18 years of age (Wittemyer *et al.*, 2013). Over the span of several years, they spend less and less time in the company of family groups (Evans and Harris, 2008), and more time in what have been referred to as "bull areas," or distinct places where bulls feed away from families (Moss, 1988). This equates to spending less time in areas that are most heavily contaminated by dung, which is the source of infective larvae (Condy, 1974), so a male's chances of contracting strongylids via exposure should decline as his dispersal becomes more complete.

Regarding environmental exposure related to space use, the finding that elephants who spend less time within reserves have higher strongylid loads could be related to the fact that strongylid larvae survive better in certain soils (Condy, 1974). Sun *et al.* (2018) found that the strongylid infection of cattle (*Bos taurus*) was correlated with where they grazed. As soil's ability to hold water decreased, vegetation cover decreased and soil compaction increased, cattle were more infected with strongylids (Sun *et al.*, 2018). Community conservancies and other areas surrounding the protected reserves in Samburu are affected by livestock grazing (Ihwagi *et al.*, 2015). Resulting differences in vegetation cover and soil properties outside versus within reserves could be facilitating the survival of infective strongylid larvae, which can survive up to 90 days in soil with small particle size (Condy, 1974). If this is true, it would suggest that human modification of landscapes has cascading effects that can amplify parasitic diseases in wildlife (Buma, 2015). Elephants spending more time outside of reserves may also have lowered immunity against strongylids since their access to the highest quality resources within protected areas is less (Wittemyer *et al.*, 2007b), and they are more exposed to the threat of humans, altering their activity patterns (Wittemyer *et al.*, 2016) and likely increasing stress.

The role of sociality and social disturbance in determining strongylid infection

Our findings add support for the idea of Rimbach *et al.* (2015) that proximity-based social networks can be too coarse to show the effect of sociality on GI nematode loads. None of the social network metrics, which were derived from proximity-based associations, showed any effect on strongylid load in our study. However, when using focal follow behavioral data as a measure of social integration, we found support for the idea that social behavior impacts strongylid infection. Elephants who were more frequently a recipient of aggression had lower strongylid loads (Table 1.5A, Figure 1.4), likely due to the fact that they spend more time on the periphery of social groups (Goldenberg and Wittemyer, 2018), and thus would be spending less time in localities heavily contaminated by the dung of other individuals, decreasing their exposure to infective larvae that originate in dung boli (Condy, 1974). Strongylid larvae take weeks to develop and become infective (Condy, 1974), but family groups frequent "favorite" areas where older elephant dung is concentrated, such as under large trees that provide shade for resting (Goldenberg and Wittemyer, 2017).

The estimated effect of whether an elephant had left her natal family is interesting, because when an elephant leaves her natal family, she is the recipient of more aggression (Goldenberg and Wittemyer, 2017, 2018). We suspect this is why Models 6 and 7, which do not directly account for behavior, indicate that elephants who remain with their natal family shed more strongylid eggs (Table 1.5B, Figure 1.5), but that effect disappears when the effect of aggression from other elephants is directly accounted for in Model 4 (Table 1.5A). Overall, social disruption appears to increase social isolation for surviving orphans who are with unrelated elephants, decreasing their exposure to strongylid infection. We will analyze stress hormones of the same isolated orphans in future work, to discover whether increased aggression from other individuals measurably increases their stress, in which case their susceptibility to parasites should also increase (Sapolsky, 2004). If they are more susceptible, socially-mediated exposure may play a greater role in strongylid transmission than susceptibility.

Importantly, physical contact did not correlate with strongylid loads. We were able to parse behaviors according to those involving physical contact (be they affiliative or aggressive), all affiliative behaviors with or without physical contact, and all aggressive behaviors with or without physical contact (Table 1.2). Accordingly, our results demonstrate that the correlation of strongylid loads with physical contact observed in primate studies (MacIntosh *et al.*, 2012; Rimbach *et al.*, 2015) may be indicative of nematode loads correlating with social integration rather than actual physical contact. As noted by authors, affiliative physical contact can act as a proxy for social integration (MacIntosh *et al.*, 2012).

The weak evidence that orphans from mothers who died of drought have higher strongylid loads than orphans from mothers who were illegally killed (Table 1.5B) may reflect the increase of strongylid parasitism in times of drought (Obanda *et al.*, 2011). Orphans of adult females who died from drought would have exhibited similar feeding, drinking and space use behaviors as the older females in their family groups (Moss, 1988) during a time of nutritional stress, and been similarly exposed to parasitism. It is possible they have been unable to fully recover from increased strongylid loads contracted during the drought that killed their mother.

Unexpected results

We were surprised by some results of our study. First, seasonality as measured by NDVI showed no effect, even though other studies investigating strongylid infection have shown seasonal effects (Vidya and Sukumar, 2002; Thurber *et al.*, 2011; Cizauskas *et al.*, 2015; Albery *et al.*, 2018). Potentially, repeated sampling from the same individuals caused individual variability in strongylid loads to overwhelm the effect of seasonality (Supplementary Figure A1). Or perhaps exposure and susceptibility opposed one another to mask seasonal effects; although strongylid eggs need adequate moisture to hatch (Khan *et al.*, 2015), and thus infective larvae should be more prevalent in wet seasons, hosts are presumably more susceptible during dry seasons due to harsher conditions (Thurber *et al.*, 2011). It is also possible that human modified landscapes in the study area increased larval survival further into the dry season than is normal in unaltered landscapes (Sun *et al.*, 2018).

We were again surprised by the estimated negative correlation of group size with strongylid loads in Model 3 (Table 1.5A), the model which included only calf samples. When it shows an effect, group size generally correlates positively with parasitic infection (Rifkin *et al.*, 2012), especially with contagious or fecal-oral transmitted parasites like strongylids (Côte and Poulin, 1995). However, Akinyi *et al.* (2019) also found a negative correlation between group size in wild baboons (*Papio cynocephalus*) and strongylid infection. They suggested it was due to interactions between nematodes and whipworms (Akinyi *et al.*, 2019). Due to time constraints, we lacked information on other endoparasites and intestinal organisms of elephants that may affect strongylids, such as several members of the protozoan class Ciliata (ciliates) (Eloff and van Hoven, 1980). Some intestinal ciliates are known to aid in fiber digestion (Profousová *et al.*, 2011), which enhances immune function (Schley and Field, 2002). Juvenile elephants directly ingest ciliates when they eat freshly-dropped dung of adults in their family group (Eloff and van Hoven, 1980), but this coprophagic behavior is not observed in older elephants. Fresh dung is more available as group size increases, so increased ciliate loads in calves of large groups could have resulted in the observed negative correlation between strongylid infection and group size.

Future directions

Our study did not control for differences in diet. Varying diet was found to have a large effect on parasitic worm infection in many species of lizards (Leung and Koprivnikar, 2019). Although we did not explicitly quantify diet, previous work has shown that the ratio of grass to browse elephants eat changes predictably with NDVI (Cerling *et al.*, 2006; Wittemyer *et al.*, 2009). The lack of correlation between EPG counts and NDVI suggests that dietary shifts between grass and browse do not influence strongylid loads. However, future studies should investigate whether strongylid infection varies with finer scale differences in diet. Future studies might also investigate whether social rank affects strongylid loads in African elephants, because studies have found that dominant individuals are more infected with strongylids in species such as meerkats (*Suricatta suricatta*) (Smyth and Drea, 2015). In addition, nematode parasites tend to aggregate within human populations such that 80% of them are found within 20% of individuals (Wilson *et al.*, 2002). A follow-up study could be designed to answer the question of whether this pattern exists with strongylids in elephant families.

Two follow-up studies would be especially valuable. First would be a study that tests whether soil outside of reserves is actually more contaminated with strongylid larvae than that within reserves. Soil samples from different areas could be measured for infective larvae to create a map of geographic risk, then be combined with GPS collar data to discover if EPG counts vary according to how often an elephant is found in heavily infected areas. Secondly, a future study might investigate the possible existence of a stable limit cycle in strongylid infection patterns. Lafferty and Holt (2003) suggest that such cycles may exist for parasites that are generally well-tolerated. We observed oscillations between subsequent samples of those individuals we regularly sampled (Supplementary Figure A1), and suspect such oscillation may have something to do with pulses in the egg laying of adult strongylids (Khan *et al.*, 2015). Yet because we did not sample at regular intervals, we were unable to implement time series analyses.

Conclusions

As previous studies of strongylid infection in elephants have not included individual-based social factors (Vidya and Sukumar, 2002; Thurber *et al.*, 2011; Baines *et al.*, 2015), our study makes a significant contribution to the understanding of how social factors influence strongylid infection in these animals. Overall, elephants who spent less time in locations frequented by family groups, be they males or socially isolated orphans, had lower strongylid loads. We further emphasize that movement outside of protected areas seems to increase strongylid infection in elephants. This study suggests that the human impacts of social disruption and habitat modification may have indirect effects (Buma, 2015) on parasitism in African elephants, a vulnerable species of conservation concern (IUCN, 2019) .

References

Akinyi MY, Jansen D, Habig B, Gesquiere LR, Susan C, Archie EA, Alberts SC and Archie EA (2019) *Costs and Drivers of Helminth Parasite Infection in Wild Female Baboons*. doi:10.1111/1365-2656.12994

Albery GF, Kenyon F, Morris A, Morris S, Nussey DH and Pemberton JM (2018) Seasonality of helminth infection in wild red deer varies between individuals and between parasite taxa. *Parasitology* **145** 1410–1420. doi:10.1017/s0031182018000185

Allen K, Follis T and Kistner T (1974) Ocurrence of Grammocephalus clathratus (Baird, 1868) Raillet and Henry, 1910 (Nematoda: Ancylostomatidae), in an African Elephant Imported into the United States. *Journal of Parasitology* **60** 952.

Arnold TW (2010) Uninformative Parameters and Model Selection Using Akaike's Information Criterion. *Journal of Wildlife Management* **74** 1175–1178. doi:10.2193/2009-367

Baines L, Morgan ER, Ofthile M and Evans K (2015) Occurrence and seasonality of internal parasite infection in elephants, Loxodonta africana, in the Okavango Delta, Botswana. *International Journal for Parasitology: Parasites and Wildlife* **4** 43–48. doi:10.1016/j.ijppaw.2015.01.004

Barrat A, Barthélemy M, Pastor-Satorras R and Vespignani A (2004) The Architecture of complex weighted networks. *PNAS* **101** 3737–3752. doi:10.1073/pnas.0400087101

Bates D, Mächler M, Bolker B and Walker S (2015) Fitting Linear Mixed-Effects Models using lme4. *Journal of Statistical Software* **67** 1–48.

Bivand R and Lewin-Koh N (2019) maptools: Tools for Handling Spatial Objects. R package version 0.9-5.

Bivand RS, Pebesma E and Gomez-Rubio V (2013) *Applied Statistical Analysis with R*. New

York: Springer.

Bivand R, Keitt T and Rowlingston B (2019) Bindings for the ‘Geospatial’ Data Abstraction Library. R package version 1.3-9.

Buma B (2015) Disturbance interactions: Characterization, prediction, and the potential for cascading effects. *Ecosphere* **6** 1–15. doi:10.1890/ES15-00058.1

Burnham KP and Anderson DR (2004) Multimodel Inference. *Sociological Methods & Research* **33** 261–304. doi:10.1177/0049124104268644

Cerling TE, Wittemyer G, Rasmussen HB, Vollrath F, Cerling CE, Robinson TJ and Douglas-Hamilton I (2006) Stable isotopes in elephant hair document migration patterns and diet changes. *Proceedings of the National Academy of Sciences* **103** 371–373. doi:10.1073/pnas.0509606102

Cizauskas CA, Turner WC, Pitts N and Getz WM (2015) Seasonal Patterns of Hormones, Macroparasites, and Microparasites in Wild African Ungulates: The Interplay among Stress, Reproduction, and Disease. *PLoS ONE* **10** e0120800-29.

Condy JB (1974) Observation on internal parasites in Rhodesian elephants, Loxodonta africana Blumenback 1797. *Proceedings and Transactions of the Rhodesia Scientific Association* **55** 67–99.

Côte IM and Poulin R (1995) Parasitism and group size in social animals: a meta-analysis. *Behavioral Ecology* **2** 159–165. doi:10.1093/cz/zow073

Crompton DWT and Nesheim MC (2002) Nutritional impact of intestinal helminthiasis during the human life cycle. *Annual Review of Nutrition* **22** 35–59. doi:10.1146/annurev.nutr.22.120501.134539

Csárdi G and Nepusz T (2006) *The Igraph Software Package for Complex Network Research,* *Interjournal, Complex Systems 1965*. doi:10.3724/SP.J.1087.2009.02191

Eloff AK and van Hoven W (1980) Intestinal Protozoa of the African Elephant Loxodonta Africana (Blumenbach). *South African Journal of Zoology* **15** 83–90. doi:10.1080/02541858.1980.11447691

ESRI (Environmental Systems Research Institute) (2017) ArcGIS Release 10.5. Redlands, CA.

Evans KE and Harris S (2008) Adolescence in male African elephants, Loxodonta africana, and the importance of sociality. *Animal Behaviour* **76** 779–787. doi:10.1016/j.anbehav.2008.03.019

Ezenwa VO and Worsley-Tonks KEL (2018) Social living simultaneously increases infection risk and decreases the cost of infection. *Proceedings of the Royal Society B: Biological Sciences* **285**. doi:10.1098/rspb.2018.2142

Farine DR and Whitehead H (2015) Constructing, conducting and interpreting animal social network analysis. *Journal of Animal Ecology* **84** 1144–1163. doi:10.1111/1365-2656.12418

Fournier DA, Skaug HJ, Ancheta J, Ianelli J, Magnusson A, Maunder MN, Nielsen A and Sibert J (2012) AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. *Optimization Methods and Software* **27** 233–249.

Gibbons L, Jacobs DE, Fox MT and Hansen J (2004) The RVC/FAO guide to veterinary diagnostic parasitology. McMaster egg-counting technique. Available at http://www.rvc.ac.uk/review/Parasitology/EggCount/Purpose.htm (accessed March 2015)

Ginsberg JR and Young TP (1992) Measuring association between individuals or groups in behavioural studies. *Animal Behaviour* **44** 377–379. doi:10.1016/0003-3472(92)90042-8

Goldenberg SZ (2016) Ivory poaching, sociality, and the role of behavior in conservation. Colorado State University, PhD dissertation.

Goldenberg SZ and Wittemyer G (2017) Orphaned female elephant social bonds reflect lack of access to mature adults. *Scientific Reports* **7** 14408. doi:10.1038/s41598-017-14712-2

Goldenberg SZ and Wittemyer G (2018) Orphaning and natal group dispersal are associated with social costs in female elephants. *Animal Behaviour* **143** 1–8. doi:10.1016/j.anbehav.2018.07.002

Goldenberg SZ, Douglas-hamilton I and Wittemyer G (2018) Inter-generational change in African elephant range use is associated with poaching risk , primary productivity and adult mortality. *Proceedings of the Royal Society B*. doi:10.1098/rspb.2018.0286

González-Hernández M, Rangel-Negrín A, Schoof VAM, Chapman CA, Canales-Espinosa D and Dias PAD (2014) Transmission Patterns of Pinworms in Two Sympatric Congeneric Primate Species. *International Journal of Primatology* **35** 445–462. doi:10.1007/s10764-014-9751-y

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D and Moore R (2017) Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* **202** 18–27. doi:10.1016/j.rse.2017.06.031

Handcock M, Hunter D, Butts C, Goodreau S, Krivitsky P and Morris M (2018) ergm: Fit, Simulate and Diagnose Exponential-Family Models for Networks. The Statnet Project. R package version 3.9.4.

Hijmans RJ (2019) Introduction to the 'Raster' Package (Version 2 . 8-19).

Hunter D, Handcock M, Butts C, Goodreau S and Morris M (2008) ergm: A Package to Fit, Simulate and Diagnose Exponential-Family Models for Networks. *Journal of Statistical*

Software **24** 1–29.

Ihwagi FW, Wang T, Wittemyer G, Skidmore AK, Toxopeus AG, Ngene S, King J, Worden J, Omondi P and Douglas-Hamilton I (2015) Using poaching levels and elephant distribution to assess the conservation efficacy of private, communal and government land in northern Kenya. *PLoS ONE* **10**. doi:10.1371/journal.pone.0139079

IUCN (2019) The IUCN Red List of Threatened Species. Version 2019-3. http://www.iucnredlist.org (accessed September 2019).

Khan MN, Sajid MS, Khan MK, Iqbal Z and Hussain A (2010) Gastrointestinal helminthiasis: Prevalence and associated determinants in domestic ruminants of district Toba Tek Singh, Punjab, Pakistan. *Parasitology Research* **107** 787–794. doi:10.1007/s00436-010-1931-x

Khan MA, Roohi N and Rana MAA (2015) Strongylosis in Equines : A Review. *The Journal of Animal and Plant Sciences* **25**(1) 1-9.

Kim M and Kyung M (2017) Maximum likelihood estimation of Logistic random effects model. *Korean Journal of Applied Statistics* **30** 957–981. doi:10.5351/KJAS.2017.30.6.957

Krause J, Croft DP and James R (2007) Social network theory in the behavioural sciences: Potential applications. *Behavioral Ecology and Sociobiology* **62** 15–27. doi:10.1007/s00265-007-0445-8

Lafferty KD and Holt RD (2003) How should environmental stress affect the population dynamics of disease? *Ecology Letters* **6** 654–664. doi:10.1046/j.1461-0248.2003.00480.x

Lester HE and Matthews JB (2014) Faecal worm egg count analysis for targeting anthelmintic treatment in horses: Points to consider. *Equine Veterinary Journal* **46** 139–145. doi:10.1111/evj.12199

Leung TLF and Koprivnikar J (2019) Your infections are what you eat: How host ecology shapes the helminth parasite communities of lizards. *Journal of Animal Ecology* **88** 416–426. doi:10.1111/1365-2656.12934

Levecke B, Behnke JM, Ajjampur SSR, Albonico M, Ame SM, Charlier J, Geiger SM, Hoa NTV, Ngassam RIK, Kotze AC *et al.* (2011) A comparison of the sensitivity and fecal egg counts of the McMaster egg counting and Kato-Katz thick smear methods for soil-transmitted helminths. *PLoS Neglected Tropical Diseases*. doi:10.1371/journal.pntd.0001201

Lynsdale CL, dos Santos DJF, Hayward AD, Mar KU, Htut W, Aung HH, Soe AT and Lummaa V (2015) A standardised faecal collection protocol for intestinal helminth egg counts in Asian elephants, Elephas maximus. *International Journal for Parasitology: Parasites and Wildlife* **4** 307–315. doi:10.1016/j.ijppaw.2015.06.001

Lynsdale CL, Mumby HS, Hayward AD, Mar KU and Lummaa V (2017) Parasite-associated mortality in a long-lived mammal: Variation with host age, sex, and reproduction. *Ecology and Evolution* **7** 10904–10915. doi:10.1002/ece3.3559

MacIntosh AJJ, Jacobs A, Garcia C, Shimizu K, Mouri K, Huffman MA and Hernandez AD (2012) Monkeys in the Middle: Parasite Transmission through the Social Network of a Wild Primate. *PLoS ONE* **7** 15–21. doi:10.1371/journal.pone.0051144

Maizels RM, Hewitson JP and Smith KA (2012) Susceptibility and immunity to helminth parasites. *Current Opinion in Immunology* **24** 459–466. doi:10.1016/j.coi.2012.06.003

Mclean AER, Kinsella JM, Chiyo P, Obanda V, Moss C and Archie A (2012) Genetic identification of five strongyle nematode parasites in wild African elephants (Loxodonta africana). *Journal of Wildlife Diseases* **48** 707–716.

Moss C (1988) *Elephant Memories: Thirteen Years in the Life of an Elephant Family*. Chicago: The University of Chicago Press.

Obanda V, Iwaki T, Mutinda NM and Gakuya F (2011) Gastrointestinal Parasites and Associated Pathological Lesions in Starving Free-Ranging African Elephants. *South African Journal of Wildlife Research* **41** 167–172. doi:10.3957/056.041.0203

Pagano AM and Arnold TW (2009) Detection Probabilities for Ground-Based Breeding Waterfowl Surveys. *Journal of Wildlife Management* **73** 392–398. doi:10.2193/2007-411

Pebesma E and Bivand R (2005) Classes and Methods for Spatial Data in R.: *R News* **5**(2). Available at https://cran.r-project.org/doc/Rnews/.

Pihl TH, Nielsen MK, Olsen SN, Leifsson PS and Jacobsen S (2018) Nonstrangulating intestinal infarctions associated with Strongylus vulgaris: Clinical presentation and treatment outcomes of 30 horses (2008–2016). *Equine Veterinary Journal* **50** 474–480. doi:10.1111/evj.12779

Prince SD and Goward SN (1995) Global Primary Production: A Remote Sensing Approach. *Journal of Biogeography* **22** 815–835. doi:10.2307/2845983

Profousová I, Mihaliková K, Laho T, Váradyová Z, Petrželková KJ, Modrý D and Kišidayová S (2011) The ciliate, Troglodytella abrassarti, contributes to polysaccharide hydrolytic activities in the chimpanzee colon. *Folia Microbiologica* **56** 339–343. doi:10.1007/s12223-011-0053-x

Rifkin JL, Nunn CL and Garamszegi LZ (2012) Do animals living in larger groups experience greater parasitism? A meta-analysis. *American Naturalist* **180** 70–82. doi:10.1086/666081

Rimbach R, Link A, Bisanzio D, Gillespie TR, Galvis N and Di Fiore A (2015) Brown spider monkeys (Ateles hybridus): a model for differentiating the role of social networks and physical contact on parasite transmission dynamics. *Philosophical Transactions of the Royal Society B: Biological Sciences* **370** 20150179–20150179. doi:10.1098/rstb.2015.0179

Sánchez CA, Becker DJ, Teitelbaum CS, Barriga P, Brown LM, Majewska AA, Hall RJ and Altizer S (2018) On the relationship between body condition and parasite infection in wildlife: a review and meta-analysis. *Ecology Letters* **21** 1869–1884. doi:10.1111/ele.13160

Sapolsky RM (2004) *Why Zebras Don't Get Ulcers*. New York: Owl Book/Henry Holt and Co.

Schley PD and Field CJ (2002) The immune-enhancing effects of dietary fibres and prebiotics. *British Journal of Nutrition* **87** S221–S230. doi:10.1079/bjn/2002541

Seivwright LJ, Redpath SM, Mougeot F, Watt L and Hudson PJ (2004) Faecal egg counts provide a reliable measure of Trichostrongylus tenuis intensities in free-living red grouse Lagopus lagopus scoticus . *Journal of Helminthology* **78** 69–76. doi:10.1079/joh2003220

Skaug H, Fournier D, Bolker B, Magnusson A and Nielsen A (2016) Generalized Linear Mixed Models using 'AD Model Builder'. R package version 0.8.3.3.

Smyth KN and Drea CM (2015) Patterns of parasitism in the cooperatively breeding meerkat: a cost of dominance for females. *Behavioral Ecology* **27** 148–157. doi:10.1093/beheco/arv132

Sun P, Wronski T, Bariyanga JD and Apio A (2018) Gastro-intestinal parasite infections of Ankole cattle in an unhealthy landscape: An assessment of ecological predictors. *Veterinary Parasitology* **252** 107–116. doi:10.1016/j.vetpar.2018.01.023

Thurber MI, O'Connell-Rodwell CE, Turner WC, Nambandi K, Kinzley C, Rodwell TC, Faulkner CT, Felt S a and Bouley DM (2011) Effects of rainfall, host demography, and musth on Strongyle fecal egg counts in African elephants (Loxodonta africanna) in Namibia. *Journal of Wildlife Diseases* **47** 172–181. doi:10.7589/0090-3558-47.1.172

Vanderwaal KL, Obanda V, Omondi GP, McCowan B, Wang H, Fushing H and Isbell LA (2016) The strength of weak ties and helminth parasitism in giraffe social networks. *Behavioral Ecology* **27** 1190–1197. doi:10.1093/beheco/arw035

Venables WN and Ripley BD (2002) *Modern Applied Statistics with S.* New York: Springer.

Vidya TNC and Sukumar R (2002) The effect of some ecological factors on the intestinal parasite loads of the Asian elephant (Elephas maximus) in southern India. *Journal of Biosciences* **27** 521–528. doi:10.1007/BF02705050

Wickham H (2007) reshape_Rmanual.pdf. *Journal of Statistical Software* **21** 1–20. doi:10.18637/jss.v021.i12

Wijeyamohan S, Treiber K, Schmitt D and Santiapillai C (2014) A visual system for scoring body condition of Asian elephants (Elephas maximus). *Zoo Biology* **34** 53–59. doi:10.1002/zoo.21181

Wilson K, Bjørnstad ON, Dobson AP, Merler S, Poglayen G, Randolf SE, Read AF and Skorping A (2002) Heterogeneities in macroparasite infections: patterns and processes. In *The Ecology of Wildlife Diseases*, pp 6–44. doi:10.1.1.17.8839

Wittemyer G (2001) The elephant population of Samburu and Buffalo Springs National Reserves, Kenya. *African Journal of Ecology* **39** 357–369. doi:10.1046/j.1365-2028.2001.00324.x

Wittemyer G, Daballen D, Rasmussen H, Kahindi O and Douglas-Hamilton I (2005a) Demographic status of elephants in the Samburu and Buffalo Springs National Reserves, Kenya. *African Journal of Ecology* **43** 44–47. doi:10.1111/j.1365-2028.2004.00543.x

Wittemyer G, Douglas-Hamilton I and Getz WM (2005b) The socioecology of elephants: Analysis of the processes creating multitiered social structures. *Animal Behaviour* **69** 1357–

1371. doi:10.1016/j.anbehav.2004.08.018

Wittemyer G, Barner Rasmussen H and Douglas-Hamilton I (2007a) Breeding phenology in relation to NDVI variability in free-ranging African elephant. *Ecography* **30** 42–50.

Wittemyer G, Getz WM, Vollrath F and Douglas-Hamilton I (2007b) Social dominance, seasonal movements, and spatial segregation in African elephants: A contribution to conservation behavior. *Behavioral Ecology and Sociobiology* **61** 1919–1931. doi:10.1007/s00265-007-0432-0

Wittemyer G, Cerling TE and Douglas-Hamilton I (2009) Establishing chronologies from isotopic profiles in serially collected animal tissues: An example using tail hairs from African elephants. *Chemical Geology* **267** 3–11. doi:10.1016/j.chemgeo.2008.08.010

Wittemyer G, Daballen D and Douglas-Hamilton I (2013) Comparative Demography of an At-Risk African Elephant Population. *PLoS ONE* **8**. doi:10.1371/journal.pone.0053726

Wittemyer G, Keating LM, Vollrath F and Douglas-Hamilton I (2017) Graph theory illustrates spatial and temporal features that structure elephant rest locations and reflect risk perception. *Ecography* **40**. doi:10.1111/ecog.02379

Zuk M and McKean KA (1996) Sex differences in parasite infections: Patterns and processes. *International Journal for Parasitology* **26** 1009–1024. doi:10.1016/S0020-7519(96)00086-0

CHAPTER 2: Poaching of African elephants indirectly decreases population growth through lowered orphan survival[2]

Introduction

Prolonged maternal care is important to the well-being of many long-lived mammals (Clutton-Brock, 1991). Mothers of these species continue to provide defense against predators and aggression, improve access to resources, and impart knowledge to their offspring after they are no longer nursing (Cheney, 1977; Sherman, 1977; McComb *et al.*, 2001; Brookshier and Fairbanks, 2003; Brent *et al.*, 2015). These benefits are crucial because studies have shown that orphans of some species like spotted hyenas (*Crocuta crocuta*), chimpanzees (*Pan troglodytes*), red deer (*Cervus elaphus*) and killer whales (*Orcinus orca*) survive less than nonorphans even if maternal death occurs post-weaning (Watts *et al.*, 2009; Foster *et al.*, 2012; Andres *et al.*, 2013; Stanton *et al.*, 2020). However, the effect of reduced orphan survival on overall population growth has not been measured in wildlife systems (but for a model with human data, see Pavard and Branger, 2012) .

Concerningly, orphan death may contribute to the decline of mammal populations undergoing poaching or hunting that targets adults, as these practices can result in an atypically large number of orphans. Furthermore, orphan survival may become more important during periods when adults are dying at higher rates because shifts in environmental conditions, such as increased poaching and drought, can alter the contribution of vital rates to population growth

[2]Adapted from: Parker, J.M., Webb, C.T., Daballen, D., Goldenberg, S.Z., Lepirei, J., Letitiya, D., Lolchuragi, D., Leadismo, C., Douglas-Hamilton, I., and Wittemyer, G. In press. *Current Biology*.

(Coulson *et al.*, 2005). Exploring the effect of such shifts is relevant because wildlife populations undergo different levels of poaching and/or hunting.

We sought to quantify the effect of lowered orphan survival on population growth for a long-lived mammal species of conservation concern, the African savanna elephant (*Loxodonta africana africana*) (Moss, 1988; Gobush *et al.*, 2021). Elephants are highly social, and post-weaning maternal care plays an important role in elephant society (Lee, 1987; Moss, 1988; Goldenberg and Wittemyer, 2017, 2018). African elephants' IUCN conservation status is endangered due to habitat loss and poaching; the latter targets both male and female adults for their large ivory tusks (Gobush *et al.*, 2021). Understanding how elephant orphaning and subsequent survival affect population dynamics could improve efforts to conserve this ecologically and economically important species (Bond, 2008; Pringle *et al.*, 2015; Naidoo *et al.*, 2016; Sitters *et al.*, 2020). Moreover, determining the indirect effects of adult death can increase our understanding of the relationship between population dynamics and social behavior, relevant to other social mammal species of conservation concern.

We used 19 years of individual-based demographic data from a long-term monitoring project in Samburu, Kenya (Wittemyer, 2001; Wittemyer *et al.*, 2005a, 2013) to achieve three main objectives: 1) quantify survival probabilities of both nursing and weaned orphans in the Samburu elephant population and compare with age-matched nonorphan survival probabilities, 2) model the response of population growth to the probability of being orphaned (i.e. orphaning probability) and orphan survival using empirically derived parameters, and 3) examine how orphan survival, and the response of population growth to orphaning probability and orphan survival, differ during periods of less versus more poaching.

Methods

Study area and population

Data collection for our study took place in the Samburu and Buffalo Springs Reserves of Kenya. These reserves lie just north of the equator at 0.3 – 0.8° N and 37.0 – 38.0° E, separated by a semi-permanent river called the Ewaso N'giro (Wittemyer *et al.*, 2013). Together they encompass 220 km^2 of semiarid terrain (Wittemyer *et al.*, 2013). Rainfall in the ecosystem averages 350 mm per year, usually falling during two wet seasons from November – December and April – May (Wittemyer *et al.*, 2013). The end of September / beginning of October marked the most consistent separation between dry and wet seasons across study years (Wittemyer *et al.*, 2013), therefore we structured our analyses by designating years ecologically as beginning on the calendar date October 1 and ending on calendar date September 30. For example, data from October 1, 1999 – September 30, 2000 were binned together as an ecological year of 2000. Unless otherwise specified, henceforth when referencing year(s) we are referring to ecological year(s).

The elephant population using the reserves (hereafter the "Samburu population") has been studied since 1998 (Wittemyer, 2001). Over 1,000 elephants have been identified. For this study, known elephants were monitored daily between October 1 1998 – September 30 2017 by long-term researchers who recognized each elephant individually using age, sex, ear markings, tusk configurations and other notable features (Douglas-Hamilton, 1972; Wittemyer *et al.*, 2013) pictured in a continually updated photo identification file. Once a group of elephants was found, each individual was recorded, and the accuracy of the record rated according to whether observers were certain they could record every individual present (Wittemyer *et al.*, 2005b).

Demographic data to determine ages, births and deaths

At the beginning of the long-term study, adult ages were estimated using shoulder heights and physical appearances according to guides established from molars of dead elephants (Laws, 1966; Moss, 1996). Later analysis using dental molds of darted Samburu individuals found these age estimates were accurate to within +/- 3 years for 75% and +/- 5 years for 95% of measured individuals (Rasmussen *et al.*, 2005). Due to more distinguishable size and age markers for calves younger than 10 years old, it was easy to estimate their age within 1-2 years (Moss, 1996). We knew ages for calves born during the study period because newborn calves are generally sighted within three weeks or less of birth (Wittemyer *et al.*, 2013).

Most elephant families included in our study were seen at least once a month and usually multiple times a week, therefore we considered females and non-dispersing male calves as dead if their mother and core family group were recorded without them for three consecutive observations when all group members were seen (Wittemyer *et al.*, 2013). Carcasses reported by the community or discovered by the monitoring team confirmed death for roughly a third of individuals (Wittemyer *et al.*, 2013).

Sampled Individuals

Since the Samburu and Buffalo Springs Reserves encompass less than 10% of the area used by the Samburu population (Wittemyer *et al.*, 2005a), we included only elephants who frequented the reserves for this study. We also included only females because males disperse between the ages of 5 and 18 (Wittemyer *et al.*, 2013), making it more difficult to track their mortality and reproductive output. Calves were born with a sex ratio of 64 males: 77 females throughout the study period, or roughly 4 males: 5 females, with a total of 705 calves, 320 males and 385 females. Importantly, because the assumption that calves were born with a sex ratio of

1:1 was not met, this means we assumed male survival and reproduction do not affect population growth dynamics (Caswell, 2001).

Our sample size over the 19 years totaled 645 female individuals. Among this sample of focal females, one family of 8 individuals was truncated from the sample in 2016 on account of a range shift out of the core study area (Goldenberg *et al.*, 2018) that made them unobservable. In addition, 6 individuals comprising two families shifted their ranges into the study area and were added to the sample the year of their immigration.

An "orphan" was defined as a preparous female elephant whose mother died before the orphan reached maturity, with maturity marked by giving birth. Sometimes orphans joined unrelated families, which meant 7 unknown orphan individuals (2 young adults and 5 juveniles) entered the population at various points during this study. When these unknown orphans were continuously observed with a known family, their age was estimated following established protocols (Moss, 1996) and they were included in orphan survival calculations beginning the year they were first seen.

Increased poaching (see below for quantification of the increase) in the study area from 2009 – 2014 (Wittemyer *et al.*, 2013) generated a large number of individually known orphaned elephants. Although droughts occur relatively regularly in the semi-arid study area, there were two severe droughts during these years that also increased orphan numbers. The number of females who became orphans at some point over the study's 19 years was 162, and over half of orphaning events (57%) occurred during the 6 years of heavy poaching and two severe droughts spanning 2009 to 2014.

Calculation of annual vital rates

We organized individuals into stage classes for each year of the study by birth year assuming a post-breeding, or retrospective, census (Caswell, 2001). We defined the stage classes (Figure 2.1) according to elephant life history: elephants are nutritionally dependent upon their mother until the age of 2, are juveniles between the ages of 3 and 8, and give birth with an average interbirth interval of 4 years beginning anywhere from age 9 to 18 (Wittemyer *et al.*, 2013). Adult females are in their prime from ages 19 to 35, and tend to lead families starting around age 36, meaning their presence at that age is especially important to the well-being of their family (McComb *et al.*, 2001). Although we know survival and fertility significantly drop around the age of 50 years in African elephants (Dominy *et al.*, 1998), selective poaching (Wittemyer *et al.*, 2013; Jones *et al.*, 2018) meant our annual sample size of females >50 years old (range: 1 to 15, mean 5.89, Supplementary Table A1) was not large enough to reasonably estimate average vital rates for an oldest stage class of >50 years. Therefore we binned the oldest females with individuals aged 36 – 50 (Figure 2.1).

We included orphaned individuals in separate stage classes. Although transitions between life history stages were based on age, transitions from nonorphan to orphan stages were event-based, occurring if an elephant's mother died when they were in the 0-2 (henceforth "calf") or 3-8 (henceforth "juvenile") stage class, or in the 9-18 (henceforth "young adult") class if they had not yet given birth. Orphans in the young adult stage class reentered a common pool with nonorphans when they turned 19 years old (Figure 2.1) because we do not yet have enough data on older orphan cohorts to know if orphan vital rates differ later in life. Population dynamics were calculated using a common stage-structured model,

$$\mathbf{n}(y+1) = \mathbf{A}\mathbf{n}(y), \tag{1}$$

where **n**(y) is the vector of abundances in each stage at year y (Caswell, 2001) and **A** is a projection using vital rates to estimate abundances for each stage class in year y +1, as depicted in Supplementary Figure 2.1 (see supplemental information for more about the projection matrix).

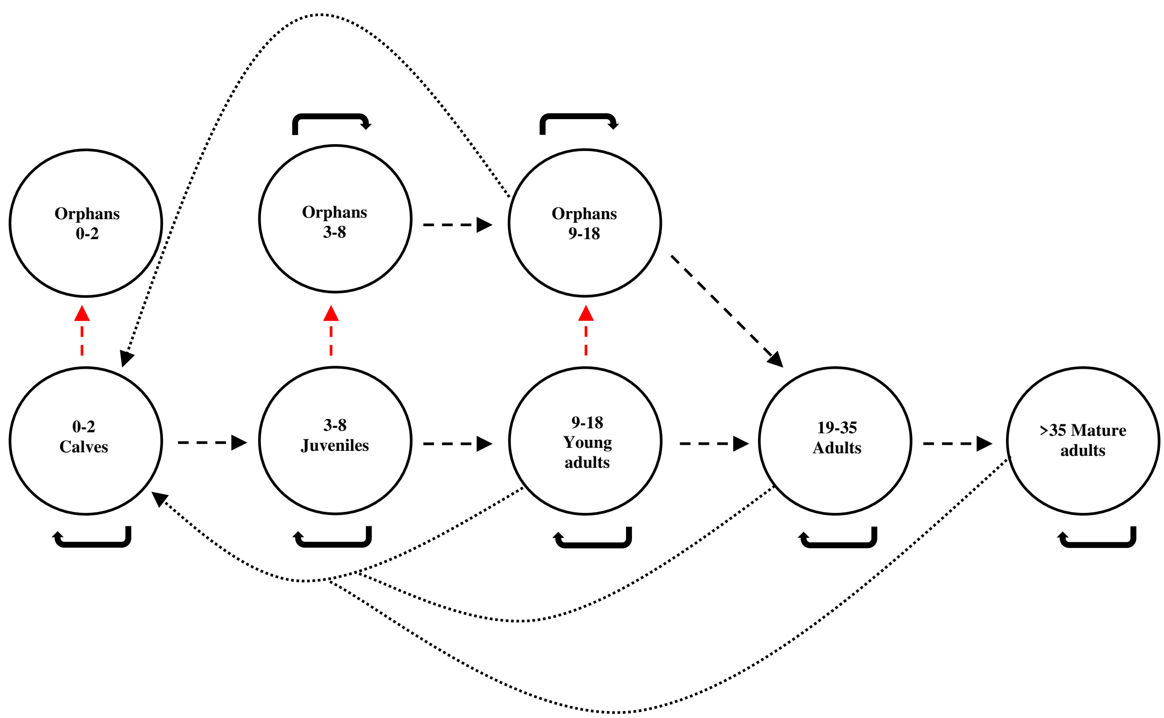


Figure 2.1: Life cycle diagram for Samburu's elephants. Dashed arrows represent transitions, self-looping solid arrows represent survival, and long dotted arrows represent fertility. The red dashed arrows represent orphaning, i.e. transitions into an orphan class. There is no transition arrow from the orphan 0-2 to the orphan 3-8 stage class because 0-2 dependent orphan calves have never survived.

Assuming vital rates are a function of the aforementioned stages (Caswell, 2019), we calculated annual vital rates for orphan and nonorphan classes, appropriately discounting any lost individuals and / or individuals who had not yet entered the population (as discussed above in the "Sampled Individuals" section) from denominators of the following equations. Equation 2 calculated survival probability, S_x, for nonorphan stage x in year y, where n(y) denotes the number of nonorphans alive at census y and p(y) denotes the number of nonorphan individuals at y – 1 orphaned over the course of y:

$$S_x(y) = \frac{n(y)}{n(y-1) - p(y)} \quad . \tag{2}$$

Survival probabilities of older stages were calculated in the same way, but the denominators of the equations differed as they did not involve the subtraction of orphaned individuals, i.e. with i equal to number of individuals in stage x:

$$S_x(y) = \frac{i(y)}{i(y-1)} \quad . \tag{3}$$

Equation 4 calculated survival probability, V_x, for orphan stage x with o(y) equal to the number of orphans alive at census y:

$$V_x(y) = \frac{o(y)}{o(y-1) + p(y)} \quad . \tag{4}$$

Age-based transition probability, T_x, from nonorphan stage x into subsequent nonorphan stage x + 1 was calculated according to equation 5, where d is the number of oldest nonorphans to transition into x + 1:

$$T_x(y) = \frac{d(y)}{n(y-1) - p(y)}, \tag{5}$$

Age-based transition probabilities, T_x, of older stages were calculated in the same way, but again the denominators of the equations differed as they did not involve the subtraction of orphaned individuals. Equation 6 calculated the age-based transition probability, U_x, from orphan stage x into subsequent stage x + 1, with e as the number of oldest orphans to transition into x + 1:

$$U_x(y) = \frac{e(y)}{o(y-1) + p(y)}. \tag{6}$$

All age-based transitions were multiplied by survival of the originating stage x within the projection **A** to calculate **n**(y+1), see supplemental information and Supplementary Figure A3.

Equation 7 calculated Z_x, the probability of being orphaned and moving into orphan stage x from nonorphan stage x:

$$Z_x(y) = \frac{p(y)}{n(y - 1)} \quad . \tag{7}$$

This event-based orphaning probability, Z_x, was multiplied by the survival probability of the orphan stage into which orphaned individuals were entering, V_x, within **A** (see supplemental information, Supplementary Figure A3).

Finally, we calculated the fertility $F_{9\text{-}18}$ of the nonorphan stage of ages 9-18 according to Equation 8, with c denoting the number of female calves born to nonorphans during y:

$$F_{9\text{-}18}(y) = \frac{c(y)}{n(y - 1) - p(y)} \quad , \tag{8}$$

Fertilities of the older stage classes, F_x, were calculated according to the same method with reduced denominators:

$$F_x(y) = \frac{c(y)}{i(y - 1)} \quad . \tag{9}$$

The fertility for the young adult orphan stage, $G_{9\text{-}18}$, was calculated according to Equation 10 below, with c denoting the number of female calves born to orphans during y:

$$G_{9\text{-}18}(y) = \frac{c(y)}{o(y - 1) + p(y)} \quad . \tag{10}$$

Our calculations produced 20 vital rate vectors, each corresponding to an arrow in Figure 2.1 (the 20 vital rates are also specified in Supplementary Figure A3). Vectors for most parameters consisted of 19 data points (one for each year 1999 – 2017), but we excluded data points calculated from annual sample sizes of less than 5 individuals (see Supplementary Table A1 for average annual sample size per stage class). Therefore the orphan 3-8 and orphan 9-18 vital rates had 18 and 17 data points, respectively.

Orphan and nonorphan survival probability comparisons

We compared the transformed orphan and nonorphan survival probability vectors of the juvenile and young adult stage classes by bootstrapping the means of each (Efron and Tibshirani, 1993, Appendix 3 bootstrap) and examining the degree of overlap in resulting confidence intervals. As an additional test, we ran the Kolmogorov-Smirnov (K-S) test (Massey, Jr., 1951, Appendix 3 K-S_tests) to compare the same orphan and nonorphan survival probability vectors. (We further bootstrapped the means and confidence intervals of all other vital rates, see Appendix 3 boot_other_parameters.)

Sensitivity analysis

For the sensitivity analysis, we created beta distributions for each of the 20 vital rates with MatLab's (version 2020a) Distribution Fitter App. To account for variable sample sizes (Supplementary Table A1) and because our data contained some 0 and 1 values that cannot be included when fitting a beta distribution, we transformed each data point following Smithson and Verkuilen (2006):

$$w' = \frac{w * (q - 1) + .5}{q} \quad , \tag{11}$$

with q as the number of individuals in a stage class at the end of the previous year (i.e. the number of individuals used in the denominator of calculations in equations 2 – 10), then input the transformed data vectors. Resulting alpha and beta parameters for each beta distribution can be found in Appendix 3 (beta_parameters).

Next, we created 10,000 projection matrices with each vital rate parameter drawn at random from its estimated distribution under a Latin Hypercube sampling (LHS) design using custom code (see LHS_draws and LHS_matrices of Appendix 3 for code) (McKay *et al.*, 1979; Helton and Davis, 2003; Marino *et al.*, 2008). Because orphaning probabilities are necessarily dependent on the survival of females with calves, we calculated the correlation between data points for each of the four breeding female stage classes' survival probabilities and the three orphaning probabilities, then used conditional statements to achieve similar correlations among parameter draws while still preserving the LHS design (see supplemental information for more information on correlations). The complete correlation matrix among LHS parameter draws after inducing correlation can be found in Appendix 4.

We subsequently calculated the dominant eigenvalue for each constructed projection matrix (Appendix 3 eigenvalues). Then, we standardized each vector of LHS draws for the 20 vital rate parameters and the corresponding vector of dominant eigenvalues into z-scores. We regressed the standardized eigenvalue vector, corresponding to population growth rate (λ), against the standardized 20 vital rate parameter vectors (Appendix 3, linear_regression). Resulting coefficients provided a measure of sensitivity.

Before running the regression analysis, we plotted each parameter against the dominant eigenvalues to check for non-monotonicities and did not find anything of concern (Appendix 5). Additionally, variance inflation factors calculated from the regression output were all lower than 10, indicating multicollinearity was not an intractable issue despite the correlations we induced between adult survival and orphaning probabilities (Cohen, 1977; Thompson *et al.*, 2017).

Orphan survival and sensitivity analysis for years of more versus less poaching

The larger Samburu ecosystem is designated a Convention on the International Trade in Endangered Species (CITES) site for the Monitoring of Illegal Killing of Elephants (MIKE), therefore elephant carcasses are monitored and each calendar year the Proportion of Illegally Killed Elephants (PIKE) is estimated by dividing the number of illegally killed carcasses by total carcasses found (Wittemyer *et al.*, 2013). PIKE increased from an average of 0.275 from calendar years 2002 – 2008 to 0.515 from calendar years 2009 – 2014, falling again to 0.360 from calendar years 2015 – 2017 (Wittemyer et al., in review). To analyze periods of high versus low poaching, we divided data into two groups: those from ecological years of the study corresponding to calendar years with less (1999 – 2008 and 2015 – 2017) and more (2009 – 2014) illegal killing. We then compared orphan versus nonorphan survival, created vital rate beta distributions, and reran the regression sensitivity analysis separately for each period. Notably, the study system is prone to drought, and two especially severe droughts overlapped with the period of higher PIKE from 2009 - 2014 and contributed to the larger number of adult deaths as mentioned above (Wittemyer *et al.*, 2013).

To ensure we were comparing a period of growth versus a period of decline, especially given the slight discrepancy in calendar versus ecological years, we calculated mean growth rates experienced by the population for all (ecological) years, for the designated period of less poaching, and for the designated period of more poaching by creating 17 projection matrices from the transformed data vital rate vectors, using only years during which all stage classes had an adequate sample size. We then calculated the dominant eigenvalue (λ) associated with each matrix, and bootstrapped the means and confidence intervals of all 17 eigenvalues, the 11 eigenvalues corresponding to years of less poaching, and the 6 eigenvalues corresponding to years of more poaching (Appendix 3, lambdas).

Results

Survival probabilities of orphan and nonorphan elephants

The bootstrapped means and confidence intervals of all 20 vital rates are shown in Table 2.1. Dependent orphan calves had very different survival to nonorphan calves, as they never survived without human intervention (Figure 2.2A). Juvenile orphans likewise had lower survival probabilities than nonorphans, although confidence intervals overlapped during the period of more poaching (Figure 2.2B). The K-S test statistic comparing these survival probabilities demonstrated significant differences across all years of the study ($D = 0.737$, $p < 0.001$) and during years with less poaching ($D = 1.000$, $p < 0.001$), but no difference during years with more poaching ($D = 0.333$, $p = 0.810$).

It is less certain whether young adult orphans have differing survival to nonorphans, as confidence intervals overlapped, especially during the period with more poaching (Figure 2.2C). However, the overlap was slight for the period with less poaching, suggesting orphans had a lower probability of survival during those years. K-S tests showed no difference in survival across all years of the study ($D = 0.362$, $p = 0.147$), a significant difference for the period of less poaching ($D = 0.546$, $p=0.035$), and no difference for the period of more poaching ($D = 0.333$, $p = 0.810$).

Response of population growth rate to orphaning and orphan survival

The bootstrapped mean λ experienced by the Samburu population over all years of the study was 1.000 (95% CI 0.980, 1.016), indicating a stable population. Sensitivity analysis results showed that λ varied negatively with orphaning probabilities, and positively with orphan

Table 2.1: Bootstrapped means and 95% confidence intervals (CIs) of vital rates for each stage class for all years, years of less poaching, and years of more poaching. Letters indicate overlap in CIs across each row, with the same letter indicating overlap.

Age range	Parameter	Bootstrapped Mean [95% Confidence Interval]		
		All years	**Less poaching**	**More poaching**
0-2	nonorphan survival	0.951 [0.917, 0.968] a	0.970 [0.954, 0.979] a	0.912 [0.844, 0.961] a
	orphan survival	0	0	0
	transition to 3-8	0.450 [0.371, 0.533] a	0.466 [0.398, 0.534] a	0.418 [0.236, 0.667] a
	orphaning probability	0.032 [0.025, 0.046] a	0.026 [0.020, 0.033] a	0.045 [0.028, 0.081] a
3-8	nonorphan survival	0.965 [0.939, 0.980] a	0.988 [0.984, 0.992] b	0.915 [0.878, 0.952] a
	orphan survival	0.860 [0.820, 0.892] a	0.847 [0.795, 0.885] a	0.886 [0.823, 0.935] a
	nonorphan transition to nonorphan 9-18	0.133 [0.109, 0.162] a	0.138 [0.105, 0.173] a	0.123 [0.092, 0.181] a
	orphan transition to orphan 9-18	0.311 [0.256, 0.369] a	0.299 [0.230, 0.381] a	0.334 [0.235, 0.404] a
	orphaning probability	0.051 [0.037, 0.070] a	0.037 [0.026, 0.051] a	0.082 [0.045, 0.111] a
9-18	nonorphan survival	0.966 [0.952, 0.977] a, b	0.981 [0.972, 0.988] a	0.934 [0.919, 0.954] b
	orphan survival	0.936 [0.914, 0.953] a	0.943 [0.921, 0.963] a	0.923 [0.880, 0.951] a
	nonorphan transition to 19-35	0.080 [0.062, 0.100] a	0.069 [0.051, 0.094] a	0.104 [0.067, 0.133] a
	orphan transition to 19-35	0.054 [0.040, 0.070] a	0.060 [0.042, 0.080] a	0.044 [0.024, 0.065] a
	orphaning probability	0.040 [0.028, 0.057] a, b	0.025 [0.017, 0.036] a	0.073 [0.053, 0.100] b
	nonorphan fertility	0.082 [0.065, 0.099] a	0.083 [0.063, 0.104] a	0.080 [0.048, 0.119] a
	orphan fertility	0.093 [0.071, 0.116] a	0.097 [0.069, 0.129] a	0.085 [0.053, 0.120] a
19 – 35	survival	0.947 [0.922, 0.962] a, b	0.967 [0.956, 0.977] a	0.904 [0.864, 0.937] b
	transition to >35	0.048 [0.035, 0.064] a	0.058 [0.041, 0.075] a	0.027 [0.017, 0.050] a
	fertility	0.115 [0.085, 0.152] a	0.113 [0.082, 0.156] a	0.121 [0.056, 0.190] a
>35	survival	0.904 [0.858, 0.933] a, b	0.943 [0.923, 0.959] a	0.820 [0.745, 0.883] b
	fertility	0.129 [0.092, 0.171] a	0.130 [0.089, 0.170] a	0.129 [0.055, 0.233] a

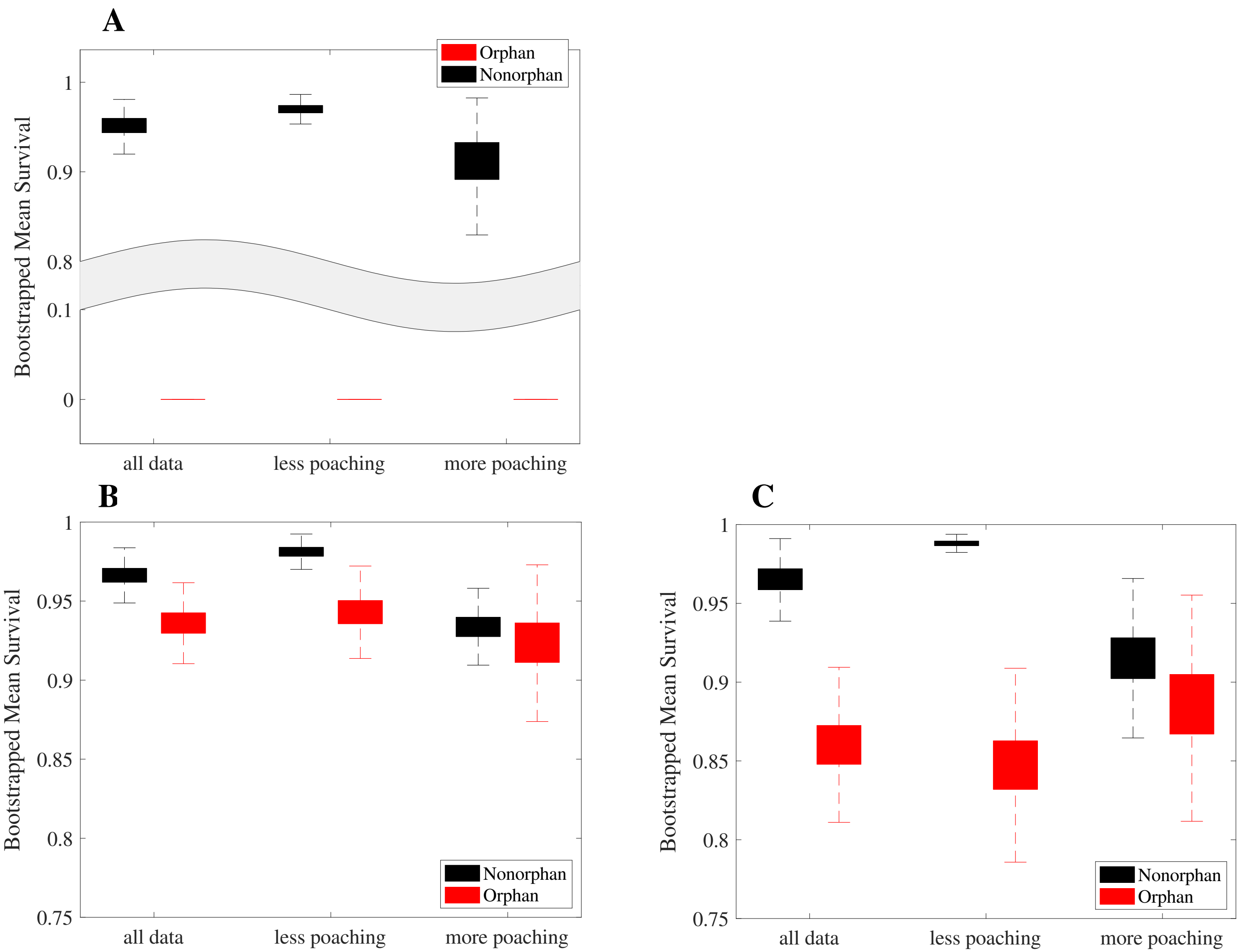


Figure 2.2: Bootstrapped means and confidence intervals for nonorphan versus orphan survival using data from all years, data from years with less poaching, and data from years with more poaching for A) 0–2-year-old calves, B) 3–8-year-old juveniles and C) 9–18-year-old young adults. Note that the y-axis of A differs from the y-axes of B and C.

survival (Supplementary Table A2A, Figure 2.3). The magnitude of the negative correlation with orphaning into the juvenile orphan stage class was greater than the positive correlation with survival probabilities of adult breeding female stage classes, which are thought of as critical to population growth (McComb *et al.*, 2001; Dominy and Ferguson, 1998) (Supplementary Table A2A, Figure 2.3). Further, λ was more sensitive to the survival of young adult orphans than to the survival of their nonorphan peers.

The mean λ experienced by the population during the period of less poaching was 1.021 (95% CI 1.012, 1.033), indicating slight growth, while the mean λ during the period of more poaching was 0.962 (95% CI 0.938, 0.989), indicating decline. The sensitivity of λ to parameters was different between these two periods (Supplementary Table A2B-C, Figure 2.3). Sensitivity to orphaning probability into the orphan juvenile and orphan young adult stages was greater for the period of less poaching (Supplementary Table A2B-C, Figure 2.3). In fact, λ was not significantly sensitive to young adult orphaning for the period of more poaching (Supplementary Table A2C, Figure 2.3). Instead, sensitivity to juvenile and young adult orphan survival increased, with λ especially sensitive to young adult orphan survival (Supplementary Table A2C, Figure 2.3). Sensitivity to calf orphaning was greater during the period of more poaching, contrary to the pattern of the other two orphaning probabilities (Supplementary Table A2B-C, Figure 2.3).

Discussion

The effect of orphan death on population dynamics for species with prolonged maternal care was previously overlooked. We sought to quantify this effect, surmising it may be particularly influential for populations with an atypically large number of orphans because adults

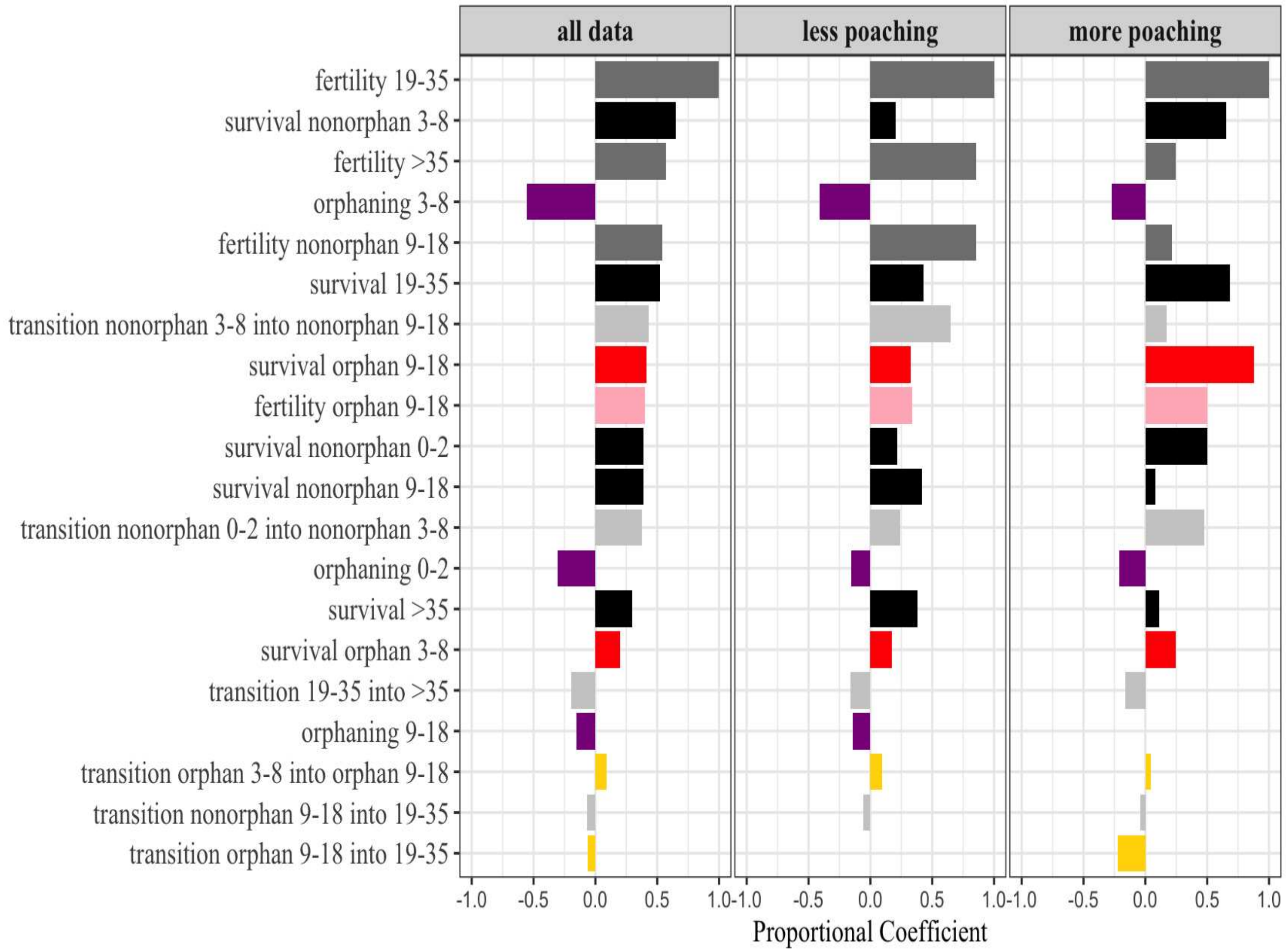


Figure 2.3: Estimated linear regression coefficients with a p-value ≤ 0.05, displayed proportionally, from the sensitivity analyses parameterized using all data, data from years with less poaching, and data from years with more poaching. Nonorphan and adult mortality parameters are shown in gray scale (black = survival, dark gray = fertility, light gray = transition), while parameters corresponding to orphan stage classes are shown in color (red = survival, pink = fertility, yellow = transition to adjacent orphan or adult stage, purple = orphaning from nonorphan into orphan). For the "all data" panel, parameters are ordered greatest to least magnitude effect size from top to bottom.

are targeted by hunters or poachers. Using a robust sensitivity analysis method with LHS sampling that both accounts for the large amount of uncertainty in biological systems and does not isolate parameters (Marino *et al.*, 2008), we found that orphaning substantively depresses population growth of wild African elephants. Our models suggested the magnitude of orphaning's impact was larger than the impacts of other parameters traditionally viewed as influential in elephants, including the survival probabilities of breeding females (Dominy *et al.*, 1998).

Quantifying wild African elephant orphan and nonorphan survival showed the estimated probability of survival for a weaned juvenile orphan (0.860) was not only less than that for nonorphans of the same age (0.965), but also less than the estimated survival for a mature adult female (0.904, Table 2.1). This is surprising because mature adults are the most subject to age-related natural mortality and have the largest tusks, making them the preferred targets of ivory poachers (Wittemyer *et al.*, 2013). Maternal care clearly sustains a higher probability of survival for weaned juveniles. Furthermore, the survival probability of weaned juvenile orphans may have been more different to nonorphans during the period of more poaching than our findings suggest (Figure 2.2B). If a poacher killed an elephant mother and we never saw her calf without her, the calf was counted in nonorphan deaths. In reality, such a calf may have survived a short while as an orphan and died before being observed without her mother. Thus our estimate of juvenile orphan survival during the period of more poaching was conservative and likely inflated while nonorphan survival was likely deflated. Also of note, increased poaching presumably equalized young adult orphan and nonorphan survival during the period of more poaching (Figure 2.2C) because poaching of younger adult individuals became more common (Wittemyer *et al.*, 2013), affecting both orphans and nonorphans. Under more natural conditions, female elephant orphans seem to suffer lower survivorship than nonorphans into young adulthood (Figure 2.2C), which is also the case for philopatric male chimpanzee orphans (Stanton *et al.*, 2020). The physiological mechanism of reduced survival in nutritionally independent juvenile and young adult elephant orphans is unknown and a subject of ongoing study.

Our model with all data showed population growth rate was more sensitive to juvenile orphaning than to the survival of adult breeding females, and slightly more sensitive to calf orphaning than to the survival of mature adult females (Supplementary Table A2A, Figure 2.3). Being orphaned into the orphan dependent calf stage represents a "dead end" for individuals, after which they can no longer contribute to population growth (Figure 2.1), and the orphan juvenile stage had the lowest survival probability among other stages. The relatively strong sensitivity to orphaning into the stages of lowest survival seems to underscore a need for exceptionally high survival in species with slow life histories like the African elephant (Roff, 1992). It also suggests breeding female survival is important largely because it sustains a higher survival probability in young elephant stages (e.g. McComb *et al.*, 2001).

Population growth responded more to orphan survival during the period of more poaching (Figure 2.3). Conversely, sensitivity to orphaning probabilities into the juvenile and young adult orphan stages was lower (Figure 2.3), indicating that when orphaning is common, growth rate responds less to orphaning itself and more to the fate of individuals who have been orphaned. This is most clearly illustrated by the lack of sensitivity to young adult orphaning probability and strong sensitivity to orphan young adult survival during the period of more poaching (Figure 2.3). Of the three orphaning probabilities, only the negative effect of the calf orphaning probability increased in magnitude with more poaching (Figure 2.3), likely because there was no survival of orphan calves on which to "offload" sensitivity in response to increased orphaning. Overall, our results indicate that a shift in parameter bounds between poaching periods altered the relationships among population growth and those parameters (Figure 2.3). The scale of poaching experienced by the Samburu population was moderate, and poaching in many populations is greater and longer lasting (Wittemyer et al., 2014), therefore population growth may be even more sensitive to orphan survival in those populations.

Our population model exposed indirect impacts of ivory poaching on African elephants by incorporating the mathematical effects of a social behavior fundamental to the species, prolonged maternal care (Lee, 1987; Moss, 1988). More widely incorporating key social behaviors into species-specific models may lead to additional new insights. For example, Pitt *et al.* (2003) weaved territorial behavior into a population model of coyotes (*Canis lupus*) and found that transient, non-territorial individuals exerted an unexpectedly large influence on population growth (Pitt *et al.*, 2003). Explicitly representing effects of social interactions among individuals may be especially important for species with slow life histories, in which social behavior fundamentally influences survival (Roff, 1992). These species are also often those of conservation concern (Webb *et al.*, 2002). A population model investigating the sensitivity of population growth to orphaning in endangered mountain gorillas (*Gorilla beringei beringei*) would be especially interesting in light of recent research showing that adoption buffers the negative effects of maternal loss for gorilla individuals (Morrison *et al.*, 2021), suggesting orphaning may not influence gorilla population growth to the same degree as in elephants.

Including only females in demographic population models is common (Caswell, 2001) and arguably reasonable for polygynous species like the African elephant, yet single-sex models assume both sexes have equal vital rates and male availability does not affect fertility (Shyu and Caswell, 2018). While our study thoroughly investigated the impacts of orphan death on population growth, we did not account for males in general or effects of orphaning on males. Accurately quantifying male elephant survival is difficult because males disperse anywhere from age 5 to 18 (Wittemyer *et al.*, 2013), and sometimes it is impossible to discern whether a male has died or merely dispersed. In species like chimpanzees, male orphan survival is lower than female orphan survival (Stanton *et al.*, 2020), indicating that sexes may be affected differently by the loss of maternal care. If this is true in elephants, our model may either under- or overestimate the immediate effects of orphaning on population growth.

As surviving orphans in Samburu age, we will compare fertility and longevity between orphans and nonorphans. This represents an important avenue for future research, as Gaillard *et al.* (2000) state that sensitivity models benefit by incorporating long-term "cohort effects" because successive life stages are not independent of previous stages. We already know orphan elephants suffer lasting social consequences in that they have less access to matriarchs and receive more aggression after being orphaned and joining a new family (Goldenberg and Wittemyer, 2017, 2018). This seems to manifest itself physiologically (Parker *et al.*, 2020), and could be associated with phenomena like faster reproductive aging and shorter lifespans, known responses to stress in Asian elephants (*Elephas maximus*) (Mumby *et al.*, 2015) and Asian and African elephants in zoos (Clubb *et al.*, 2009). Once we can empirically determine whether orphans should be kept in separate stages as adults and mature adults, we will determine whether orphaning has additional impacts on population growth. We may also observe and incorporate intergenerational effects of orphaning, as Zipple *et al.* (2021) found the offspring of orphans had reduced survival in some primate species.

Using African elephants as a model species, we have provided data-based, quantitative evidence that orphan death resulting from the death of reproductive adults is important to consider when managing and conserving species with prolonged maternal care. Collateral mortality of orphans influenced the Samburu elephant population's growth more when poaching increased, such that young adult orphan survival became particularly influential to population trends. We recommend that the effects of orphaning be modeled for other long-lived mammal populations to increase our understanding of how it affects population growth in varying environments and across species.

References

Andres D, Clutton-Brock TH, Kruuk LEB, Pemberton JM, Stopher K V. and Ruckstuhl KE (2013) Sex differences in the consequences of maternal loss in a long-lived mammal, the red deer (Cervus elaphus). *Behavioral Ecology and Sociobiology* **67** 1249–1258. doi:10.1007/s00265-013-1552-3

Bond WJ (2008) What Limits Trees in C 4 Grasslands and Savannas? . *Annual Review of Ecology, Evolution, and Systematics* **39** 641–659. doi:10.1146/annurev.ecolsys.39.110707.173411

Brent LJN, Franks DW, Foster EA, Balcomb KC, Cant MA and Croft DP (2015) Ecological knowledge, leadership, and the evolution of menopause in killer whales. *Current Biology* **25** 746–750. doi:10.1016/j.cub.2015.01.037

Brookshier JS and Fairbanks WS (2003) The nature and consequences of mother-daughter associations in naturally and forcibly weaned bison. *Canadian Journal of Zoology* **81** 414–423. doi:10.1139/z03-010

Caswell H (2001) *Matrix Population Models*. Sunderland, Massachusetts: Sinauer Associates, Inc. Publishers.

Caswell H (2019) *Sensitivity Analysis: Matrix Methods in Demography and Ecology*. Cham: Springer International Publishing. doi:10.1007/978-3-030-10534-1

Cheney DL (1977) The acquisition of rank and the development of reciprocal alliances among free-ranging immature baboons. *Behavioral Ecology and Sociobiology* **2** 303–318. doi:10.1007/BF00299742

Clubb R, Rowcliffe M, Lee P, Mar KU, Moss C and Mason GJ (2009) Fecundity and population viability in female zoo elephants: Problems and possible solutions. *Animal*

Welfare **18** 237–247.

Clutton-Brock T (1991) *The Evolution of Parental Care*. Princeton, NJ: Princeton University Press.

Cohen J (1977) *Statistical Power Analysis for the Behavioral Sciences*. New York: Academic Press.

Coulson T, Gaillard JM and Festa-Bianchet M (2005) Decomposing the variation in population growth into contributions from multiple demographic rates. *Journal of Animal Ecology* **74** 789–801. doi:10.1111/j.1365-2656.2005.00975.x

Dominy NJ, Ferguson NS and Maddock A (1998) Modelling Elephant (Loxodonta africana africana) population growth in Hluhluwe-Umfolozi Park to predict and manage limits. *South African Journal of Wildlife Research* **28** 61–67.

Douglas-Hamilton I (1972) On the ecology and behaviour of the African elephant: the elephants of Lake Manyara.

Efron B and Tibshirani RJ (1993) *An Introduction to the Bootstrap*. New York: Chapman & Hall.

Foster EA, Franks DW, Mazzi S, Darden SK, Balcomb KC, Ford JKB and Croft DP (2012) Adaptive prolonged postreproductive life span in killer whales. *Science* **337** 1313. doi:10.1126/science.1224198

Gaillard JM, Festa-Bianchet M, Yoccoz NG, Loison A and Toïgo C (2000) Temporal Variation in Fitness Components and Population Dynamics of Large Herbivores. *Annual Review of Ecology and Systematics* **31** 367–393. doi:10.1146/annurev.ecolsys.31.1.367

Gobush KS, Edwards CT., Balfour D, Wittemyer G, Maisels F and Taylor RD (2021) *Loxodonta africana* (African Savanna Elephant). In *The IUCN Red List of Threatened*

Species 2021, p e.T181008073A181022663. doi:10.2305/IUCN.UK.2021-1.RLTS.T181008073A181022663.en

Goldenberg SZ and Wittemyer G (2017) Orphaned female elephant social bonds reflect lack of access to mature adults. *Scientific Reports* **7** 14408. doi:10.1038/s41598-017-14712-2

Goldenberg SZ and Wittemyer G (2018) Orphaning and natal group dispersal are associated with social costs in female elephants. *Animal Behaviour* **143** 1–8. doi:10.1016/j.anbehav.2018.07.002

Goldenberg SZ, Douglas-Hamilton I and Wittemyer G (2018) Inter-generational change in African elephant range use is associated with poaching risk, primary productivity and adult mortality. *Proceedings of the Royal Society B: Biological Sciences* **285** 20180286. doi:10.1098/rspb.2018.0286

Helton JC and Davis FJ (2003) Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliability Engineering and System Safety* **81** 23–69. doi:10.1016/S0951-8320(03)00058-9

Jones T, Cusack JJ, Pozo RA, Smit J, Mkuburo L, Baran P, Lobora AL, Mduma S and Foley C (2018) Age structure as an indicator of poaching pressure: Insights from rapid assessments of elephant populations across space and time. *Ecological Indicators* **88**. doi:10.1016/j.ecolind.2018.01.030

Laws RM (1966) Age criteria for the African elephant. *African Journal of Ecology* **4** 1–37.

Lee PC (1987) Allomothering among African elephants. *Animal Behaviour* **35** 278–291. doi:10.1016/S0003-3472(87)80234-8

Marino S, Hogue IB, Ray CJ and Kirschner DE (2008) A methodology for performing global uncertainty and sensitivity analysis in systems biology. *Journal of Theoretical Biology* **254**

178–196. doi:10.1016/j.jtbi.2008.04.011

Massey, Jr. FJ (1951) The Kolmogorov-Smirnov test for goodness of fit. *Journal of the American Statistical Association* **46** 68–78.

McComb K, Moss C, Durant SM, Baker L and Sayialel S (2001) Matriarchs as repositories of social knowledge in African elephants. *Science* **292** 491–494. doi:10.1126/science.1057895

McKay MD, Beckman RJ and Conover WJ (1979) A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* **42** 55–61. doi:10.1080/00401706.2000.10485979

Morrison RE, Eckardt W, Colchero F, Vecellio V and Stoinski TS (2021) Social groups buffer maternal loss in mountain gorillas. *ELife* **10** 1–22. doi:10.7554/eLife.62939

Moss C (1988) *Elephant Memories: Thirteen Years in the Life of an Elephant Family*. Chicago: The University of Chicago Press.

Moss CJ (1996) Getting to Know a Population. In *Studying Elephants*, pp 58–74. Ed K Kangwana. African Wildlife Foundations.

Mumby HS, Mar KU, Hayward AD, Htut W, Htut-Aung Y and Lummaa V (2015) Elephants born in the high stress season have faster reproductive ageing. *Scientific Reports* **5** 1–11. doi:10.1038/srep13946

Naidoo R, Fisher B, Manica A and Balmford A (2016) Estimating economic losses to tourism in Africa from the illegal killing of elephants. *Nature Communications* **7**. doi:10.1038/ncomms13379

Parker JM, Goldenberg SZ, Letitiya D and Wittemyer G (2020) Strongylid infection varies with age, sex, movement and social factors in wild African elephants. *Parasitology* **147** 348–359. doi:10.1017/S0031182019001653

Pavard S and Branger F (2012) Effect of maternal and grandmaternal care on population dynamics and human life-history evolution: A matrix projection model. *Theoretical Population Biology* **82** 364–376. doi:10.1016/j.tpb.2012.01.007

Pitt WC, Box PW and Knowlton FF (2003) An individual-based model of canid populations: Modelling territoriality and social structure. *Ecological Modelling* **166** 109–121. doi:10.1016/S0304-3800(03)00130-3

Pringle RM, Kimuyu DM, Sensenig RL, Palmer TM, Riginos C, Veblen KE and Young TP (2015) Synergistic effects of fire and elephants on arboreal animals in an African savanna. *Journal of Animal Ecology* **84** 1637–1645. doi:10.1111/1365-2656.12404

Rasmussen HB, Wittemyer G and Douglas-Hamilton I (2005) Estimating age of immobilized elephants from teeth impressions using dental silicon. *African Journal of Ecology* **43** 215–219. doi:10.1111/j.1365-2028.2005.00571.x

Roff DA (1992) *The Evolution of Life Histories*. New York: Chapman & Hall.

Sherman PW (1977) Nepotism and the Evolution of Alarm Calls. *Science* **197** 1246–1253.

Shyu E and Caswell H (2018) Mating, births, and transitions: a flexible two-sex matrix model for evolutionary demography. *Population Ecology* **60** 21–36. doi:10.1007/s10144-018-0615-8

Sitters J, Kimuyu DM, Young TP, Claeys P and Olde Venterink H (2020) Negative effects of cattle on soil carbon and nutrient pools reversed by megaherbivores. *Nature Sustainability* **3** 360–366. doi:10.1038/s41893-020-0490-0

Smithson M and Verkuilen J (2006) A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. *Psychological Methods* **11** 54–71. doi:10.1037/1082-989X.11.1.54

Stanton MA, Lonsdorf E V., Murray CM and Pusey AE (2020) Consequences of maternal loss before and after weaning in male and female wild chimpanzees. *Behavioral Ecology and Sociobiology* **74** 22. doi:10.1007/s00265-020-2804-7

Thompson CG, Kim RS, Aloe AM, Jane B, Glen C, Kim RS, Aloe AM and Jane B (2017) Extracting the Variance Inflation Factor and Other Multicollinearity Diagnostics from Typical Regression Results. *Basic and Applied Social Psychology* **39** 81–90. doi:10.1080/01973533.2016.1277529

Watts HE, Tanner JB, Lundrigan BL and Holekamp KE (2009) Post-weaning maternal effects and the evolution of female dominance in the spotted hyena. *Proceedings of the Royal Society B: Biological Sciences* **276** 2291–2298. doi:10.1098/rspb.2009.0268

Webb JK, Brook BW and Shine R (2002) What makes a species vulnerable to extinction? Comparative life-history traits of two sympatric snakes. *Ecological Research* **17** 59–67. doi:10.1046/j.1440-1703.2002.00463.x

Wittemyer G (2001) The elephant population of Samburu and Buffalo Springs National Reserves, Kenya. *African Journal of Ecology* **39** 357–369. doi:10.1046/j.1365-2028.2001.00324.x

Wittemyer G, Daballen D, Rasmussen H, Kahindi O and Douglas-Hamilton I (2005a) Demographic status of elephants in the Samburu and Buffalo Springs National Reserves, Kenya. *African Journal of Ecology* **43** 44–47. doi:10.1111/j.1365-2028.2004.00543.x

Wittemyer G, Douglas-Hamilton I and Getz WM (2005b) The socioecology of elephants: Analysis of the processes creating multitiered social structures. *Animal Behaviour* **69** 1357–1371. doi:10.1016/j.anbehav.2004.08.018

Wittemyer G, Daballen D and Douglas-Hamilton I (2013) Comparative Demography of an

At-Risk African Elephant Population. *PLoS ONE* **8**. doi:10.1371/journal.pone.0053726

Wittemyer G, Northrup JM, Blanc J, Douglas-Hamilton I, Omondi P and Burnham KP (2014) Illegal killing for ivory drives global decline in African elephants. *Proceedings of the National Academy of Sciences* **111** 13117–13121. doi:10.1073/pnas.1403984111

Zipple MN, Altmann J, Campos FA, Cords M, Fedigan LM, Lawler RR, Lonsdorf E V., Perry S, Pusey AE, Stoinski TS *et al.* (2021) Maternal death and offspring fitness in multiple wild primates. *Proceedings of the National Academy of Sciences* **118** e2015317118. doi:10.1073/pnas.2015317118

CHAPTER 3: Social regulation of glucocorticoid levels in wild African elephant orphans

Introduction

The stress response of vertebrate animals is mediated by the hypothalamic-pituitary-adrenal (HPA) axis. Confronted with a stressor, the brain's hypothalamus releases the hormones arginine vasopressin and corticotropin-releasing hormone, which stimulate the pituitary gland to release adrenocorticotropic hormone (ACTH). ACTH then stimulates the adrenal glands to release glucocorticoids (GCs) into the bloodstream (Sapolsky *et al.*, 2000; Spiga *et al.*, 2014; Gjerstad *et al.*, 2018). Therefore, the traditional view is that an animal with higher circulating GCs is undergoing more stress than a similar animal with lower circulating GCs (Heim *et al.*, 2000; Sapolsky, 2004). In the short term, GCs prepare an animal's fight or flight response through enhancing processes like metabolism and cognition, while simultaneously suppressing others like reproduction (Sapolsky, 2004; Spiga *et al.*, 2014). When GC levels are sufficiently high, they bind to receptors in the brain and signal the HPA axis to stop secreting GCs (Gjerstad *et al.*, 2018). Chronic activation of the HPA axis and prolonged GC secretion can cause many health problems (Sapolsky, 2004).

There is evidence that maternal care plays a particularly important role in programming the HPA axis (Caldji *et al.*, 2000; Sapolsky *et al.*, 2000; Novak *et al.*, 2013). Laboratory Norway rats (*Rattus norvegicus*) who received more licking and grooming from their mother in the first ten days of life released less GCs when confronted with acute stressors later in life, and they developed more GC receptors in the brain, enhancing the HPA axis's negative feedback system (Liu *et al.*, 1997). Zebra finch (*Taeniopygia guttata*) adults who were deprived of maternal care as chicks secreted more GCs when faced with social isolation than adults raised by both parents

(Banerjee *et al.*, 2012), and the GC levels of weaned guinea pigs (*Cavia porcella*) placed in a novel environment increased less if their mother was present (Hennessy *et al.*, 1995). However, current understanding of maternal effects on stress pathways are derived entirely from captive studies, without insight from studies that have measured how GC levels relate to presence versus absence of maternal care in a wild population.

Close, non-maternal relationships are also important regulators of the mammalian stress response in a phenomenon referred to as "social buffering" (Hennessy *et al.*, 2009). Strong bonds with other males attenuated GC release in wild male macaques (*Macaca sylvanus*) (Young *et al.*, 2014), for instance, and the presence of a familiar companion lessened GC release following exposure to a stressor in captive male squirrel monkeys (*Saimiri sciureus*) (Stanton *et al.*, 1985). Further, an aunt or other alloparental figure lessened GC increases in infant squirrel monkeys temporarily separated from their mother (Wiener *et al.*, 1987), suggesting that non-parental familial relationships may offset stress responses associated with losing maternal care.

African elephants (*Loxodonta africana*) are a long-lived, cognitively advanced species (Moss, 1988; Douglas-Hamilton *et al.*, 2006) that offer a good opportunity to research the effects of maternal presence on HPA axis activity, and the potential for social buffering to offset stress responses that may be associated with maternal loss, in a wild setting. The mother-calf bond is fundamental to the well-being of elephant calves, even post-weaning and into young adulthood (Lee, 1987; Goldenberg and Wittemyer, 2017, 2018; Parker *et al.*, 2021). Bonds among individuals are strong; females usually remain with their family throughout life in matriarchal core groups, and close familial bonds have been associated with lower GC levels (Gobush *et al.*, 2008; Wittemyer *et al.*, 2009; Goldenberg *et al.*, 2016a). Moreover, African elephants are endangered due to habitat loss and poaching, the latter which removes maternal and other adult caregivers from familial units (Wittemyer *et al.*, 2013, 2014; Gobush *et al.*, 2021). Understanding elephants' species-specific stress response to the loss of fundamental bonds can inform conservation management decisions (Wittemyer *et al.*, 2013; McCormick and Romero, 2017).

The population of wild elephants that use the Samburu and Buffalo Springs National Reserves of Kenya (hereafter the "Samburu population") has been studied for over 20 years (Wittemyer, 2001; Wittemyer *et al.*, 2013). Poaching and severe drought from the years 2009 – 2014 killed many adult females in the Samburu population, leaving behind fragmented families and known female orphan calves (Wittemyer *et al.*, 2013; Goldenberg *et al.*, 2016). These orphans have been the focus of several studies, therefore we know they survive less than nonorphans even if they are weaned at the time of their mother's death, and that orphans who leave their family to join other families or group together with other orphans suffer increased aggression and are isolated from adult females (Goldenberg and Wittemyer, 2017, 2018; Parker *et al.*, 2021). In this study, we investigated whether the loss of maternal care correlates with increased GC secretion in wild African elephants, and whether social buffering may lessen increases in secretion. We hypothesized maternal presence and social buffering attenuate HPA axis activity in wild African elephants, thereby predicting orphans would have higher average GC levels than nonorphans, and that individuals with more adult caregivers and age mates in their core group would have lower GC levels.

Methods

Study system and subjects

The Samburu and Buffalo Springs National Reserves are unfenced reserves in Kenya, located at 0.3 – 0.8° N, 37 – 38° E and divided by a semi-permanent river called the Ewaso

Ngiro (Wittemyer, 2001). Together they encompass 220 km^2 of semi-arid terrain, with annual average rainfall of 350 mm during two wet seasons from April – May and November – December (Wittemyer *et al.*, 2013). African elephants who use the reserves are part of a long-term monitoring study that began in 1998, and to date over 1,000 elephants have been identified and are followed daily, such that detailed demographic history is available for each individual (Wittemyer *et al.*, 2013).

For this study, we selected 40 female elephant subjects for longitudinal sampling. We chose age-matched (i.e. within 4 years of age, see below) orphan/nonorphan subject pairs based on how often they were in the reserves for ease of sample collection. We also preferentially chose individuals who were part of earlier orphan studies (e.g. Goldenberg and Wittemyer, 2017). Included in the 40 subjects are 3 nonorphan offspring of primarily chosen subjects from who we collected fecal samples while waiting for their mother to produce a sample. With these 3 young calves, the subjects ranged in age from 2 – 21 years at the start of collection (see Supplementary Figure A4). Subjects were categorized as orphan (n = 25) or nonorphan (n = 15), where orphan was defined as a female whose mother died before parity (Figure 3.1A). The orphan subjects had lost their mothers at least 2 years prior to the start of our study, and of the 25 orphans, 5 had left their natal family to join an unrelated core group or form a group with other orphans after their mother's death (Figure 3.1A).

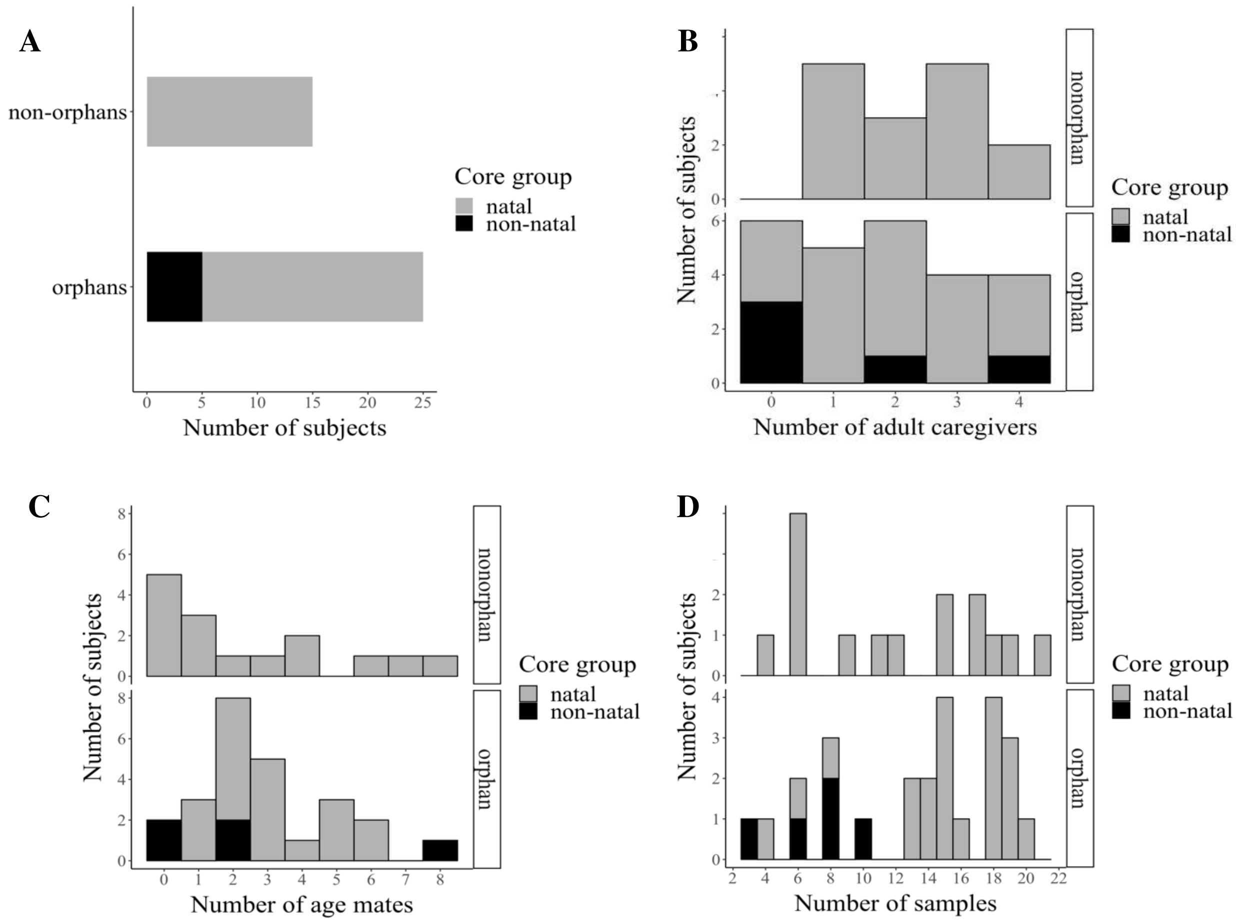


Figure 3.1: Individual-based covariates. A) Bar chart showing number of study subjects who were orphans versus nonorphans, colored according to whether they were with their natal versus non-natal core group. B-D) Histogram of study subjects according to number of adult female caregivers in their core group, number of age mates in their core group, and number of dung samples, each also separated into orphan versus nonorphan panels and colored according to natal versus non-natal core group. The 6 discarded dung samples are not included in D.

Fecal sample collection

We longitudinally sampled dung over a period of 13 months from June 2015 to July 2016, with a minimum of 2 weeks between collecting samples from the same individual. Upon finding a study subject in the field, we stayed with them until they produced a sample. Elephants in the Samburu population who frequent the reserves are habituated to and will feed or rest alongside vehicles (Wittemyer *et al.*, 2013), therefore we assumed our presence did not represent a stressor. When a sample was produced, we recorded the GPS and time dropped. Once the subject had moved away, we labeled a 30 mL plastic bottle with subject ID and date, then filled it with homogenized dung from the center of at least 2 boluses (Ganswindt *et al.*, 2005), placed it in a cool box and recorded collection time. Often dung from the same boluses was also collected into a plastic bag for strongylid fecal eggs counts (see below). Upon return to the research camp, within a maximum of 8 hours following collection, samples were stored in a freezer of approximately -10°C until analysis.

Fecal extraction and GC metabolite analysis

We shipped the resulting 520 fecal samples on dry ice to the Smithsonian Conservation Biology Institute in Front Royale, VA. There, they were lyophilized (VirTis from SP Industries, Warminster, PA) and crushed, then 0.1 g of the resulting powder was put in labeled 16 x 125mm glass tubes (Fisher Scientific; Pittsburgh, PA) and 5 mL of 80% methanol was added to each tube. The tubes were capped with rubber stops, mixed on a multi-tube vortexer (Glas-Col; Terre Haunte, IN) for 30 minutes, and centrifuged for another 20 minutes at 2500 rpm (Sorvall RC 3C Plus; Thermo Fisher Scientific, Waltham, MA). Supernatant was decanted from each into another set of labeled tubes, and the leftover pellets again suspended in 80% methanol, vortexed for 1 minute, and centrifuged for 20 minutes at 2500 rpm. Then the newly centrifuged supernatant was added to the previous supernatant tubes. The combined supernatants were dried under a fume hood, mixed with 1 ml of 100% methanol, dried again, and 1 ml of buffer solution (0.149 M NaCL, 0.1 M $NaPO_4$, pH 7.0) was added to each tube. The tubes were sonicated (Part# 08895-60; Col-Parmer, Vernon Hills, IL) for 30 seconds to fragment and dissolve particles. Each was diluted (1:5) in enzyme immunoassay (EIA) buffer (Cat. No. X065, Arbor Assays, Ann Arbor, MI, USA), and stored at -20°C before EIA analysis.

Fecal GC metabolite concentrations were measured with a double-antibody enzyme EIA containing polyclonal rabbit anti-corticosterone antibody (CJM006), which has been validated for use in elephant fecal samples (Watson *et al.*, 2013). The prepared samples (50 μL each) were added to pre-coated goat anti-rabbit IgG 96-well plates at room temperature, followed by immediate addition of corticosterone-horseradish peroxidase (25 μL, 1:20,000 dilution) and anti-corticosterone antibody (25 μL, 1:60,000 dilution). Plates were covered with microplate sealers, incubated at room temperature on an agitator (Model E6121; Eberbach Corp., Ann Arbor, MI) for 1 hour, washed four times (1:20 dilution, 20X Wash Buffer Cat. No. X007; Arbor Assays) and blotted dry. Next 100 μL of TMB (3, 3', 5, 5'-tetramethylbenzidine) (Moss Inc., Pasadena, MD) was added to each well, plates were incubated at room temperature for 30-45 minutes without agitation, then 50 μL of 1 N HCl solution was added to stop reactions. Finally, optical density was read in a plate reader at 450 nm (OPsys MR; Dynex Technolgies, Chatilly, VA).

Choice and calculation of covariates

We used data on the number of adult caregivers and age-mates within an individual's core group to test for social buffering effects. We defined "adult caregiver" as a multiparous female, given primiparous females are still young and inexperienced (some as young as 9 years old, Wittemyer *et al.*, 2013). The number of adult caregivers available in a subject's core group, f_i, ranged from 0 to 4 (Figure 3.1B). We defined "age-mate" as an undispersed male or female individual within 4 years of age because 4 years is the average interbirth interval for the Samburu population (Wittemyer *et al.*, 2013). The number of age-mates, m_i, available within a subject's core group ranged from 0 to 8 (Figure 3.1C). Orphan status, o_i, was represented as a 0/1 binary variable with 0 = nonorphan and 1 = orphan. Another binary variable, a_i, represented whether an individual was with a related core group, with 0 = with natal family and 1 = with an unrelated core group.

Additionally, we included several covariates that were factors associated with GC secretion in previous elephant studies, namely reproductive condition (e.g. Foley *et al.*, 2001), age (Oduor *et al.*, 2020), time of day (Brown *et al.*, 2010) and seasonality (Oduor *et al.*, 2020). The long-term demographic monitoring data provided precise information on reproductive condition and age. Binary 0/1 variables represented if a subject was pregnant, p_{ij}, and/or lactating, l_{ij}, versus not at each sampling event. (Supplementary Figure A4A). A subjects' precise age at each sampling event, g_{ij}, was represented as a continuous variable (Supplementary Figure A4B). We recorded the time of day a sample was produced as described above (Supplementary Figure A4C), and represented it as a continuous variable, t_j, from 0 to 1, with 0 = midnight and 1 = 23:59:59. For seasonality, we used the normalized difference vegetation index (NDVI) 16-day composite images from the moderate resolution imaging spectroradiometer (MODIS) to estimate primary productivity during the collection period (Justice *et al.*, 1998). Rasters were clipped to a core study area drawn from elephant GPS collar data (Wittemyer *et al.*, 2007), then the mean, v_j, and standard deviation, z_j, of pixel values were extracted for each sampling date (Supplementary Figure A4E). The mean was interpreted as an overall measure of productivity, and the standard deviation as a measure of vegetation predictability (Bastille-Rousseau *et al.*, 2020).

Additionally, we included as control variables the number of samples per individual, n_i (mean $\pm$ SD: 15 $\pm$ 4 samples per individual, Figure 3.1D) and the time between when a sample was dropped and placed in the cool box (Supplementary Figure A4D), s_j, in case of degradation (Lafferty *et al.*, 2019). Further, as some studies have shown effects of parasites on GC secretion in vertebrates (O'Dwyer *et al.*, 2020), and because many of our samples were paired with fecal egg counts (FECs) to estimate strongylid infection for another study (Parker *et al.*, 2020), we ran an analysis including those FECs, w_{ij}, as a covariate. The FECs (Supplementary Figure A4F) were obtained as described in Parker *et al.* (2020) using the McMaster slide method (Gibbons *et al.*, 2004). Briefly, dung taken from the same boluses as the GC samples was mixed with saltwater to float strongylid eggs, then the solution pipetted into slides with an overlain grid. The easily recognizable eggs falling within the grid were counted under a 10 X 10 microscope, and these counts entered in a standard formula to calculate the approximate number of strongylid eggs per gram of fecal matter (Gibbons *et al.*, 2004).

Statistical analysis and model selection

Prior to analysis, we discarded samples that were greater than 3 standard deviations from the mean GC concentration of the individual from which they were collected, as these outliers were likely misrepresentative and removing them greatly improved our model fit. In total, we discarded 6 of 520 samples, each from a different individual, and were left with 514 samples for the analysis described below.

We analyzed the data using a hierarchical Bayesian model with uninformative priors (see code at the end of supplemental information). One level of the model used time invariant, individual-based covariates (defined above; Figure 3.1) to estimate the mean baseline GC level for each individual:

$$\bar{y}_i \sim \text{Normal}(\mu_i, \tau_1) \qquad \text{Eqn 1}$$

$$\mu_i = \alpha + \beta_1 f_i + \beta_2 m_i + \beta_3 n_i + \beta_4 o_i + \beta_5 a_i \qquad \text{Eqn 2}$$

where $\bar{y}_i$ = mean GC concentration of individual i's samples, distributed normally with parameters μ_i = the true unknown mean baseline GC concentration of individual i and τ_1 = a precision parameter associated with measurement uncertainty and uncertainty surrounding the process by which an individual's baseline GC values are determined.

The estimated mean baseline from the first level model (Equation 2) was the intercept within the linear deterministic process model of the second level (Equation 4), which estimated effects of previously defined covariates that change with time (Supplementary Figure A4):

$$y_{ij} \sim \text{Normal}(\mu_{ij}, \tau_2) \qquad \text{Eqn 3}$$

$$\mu_{ij} = \mu_i + \gamma_1 g_{ij} + \gamma_2 l_{ij} + \gamma_3 s_j + \gamma_4 t_j + \gamma_5 v_j + \gamma_6 p_{ij} + \gamma_7 z_j \qquad \text{Eqn 4}$$

where data y_{ij}, are distributed normally with parameters μ_{ij} = the true unknown GC concentration of the sample from individual i at sampling event j, and τ_2 = a precision parameter again associated with uncertainty.

We ran our analysis in RStudio version 1.1.463 (Rstudio Team, 2016; R Core Team, 2018) using the package *rjags* version 4-10 (Plummer, 2019) with Markov-Chain Monte Carlo, running 3 parallel chains of 100,000 iterations, using 1,000 for adaptation and discarding 10,000 as burn-in. We checked convergence with Gelman-Rubin diagnostic Rc values (Gelman and Rubin, 1992; Brooks and Gelman, 1998), which were all <1.1. All covariates and GC concentration data were standardized by subtracting the mean and dividing by standard deviation ($\frac{x-\bar{x}}{\sigma}$) prior to analysis.

We selected our top model according to lowest DIC selection (Spiegelhalter *et al.*, 2002; Hooten and Hobbs, 2015), first calculating DIC for the global model, then calculating for the global model minus each variable in turn. We then calculated the DIC for the global model minus combinations of variables without which the DIC decreased, until we arrived at a model with lowest DIC among the others. A layout of our model selection process is available in Supplementary Table A5. Finally, we assessed model fit by simulating data according to the top model and graphing it with the package *bayesplot* (Gabry and Mahr, 2020), overlaying the real data (see Supplementary Figure A6).

FEC counts were available for only 464 of the 514 samples, therefore we ran a separate analysis with the subset of 464 samples to test for a correlation with strongylid infection (Parker *et al.*, 2020). This analysis had the same format but only included variables from the top model of the analysis using all samples, with the addition of the term "+ $\gamma_8 w_{ij}$" (w_{ij} described above). We calculated DIC's with and without the w_{ij} (see Supplementary Table A5).

Figures

We made Figures 3.1 and 3.3, and Supplementary Figures A4 – A5, in RStudio version 1.1.463 using ggplot2 (Rstudio Team, 2016; Wickham, 2016; R Core Team, 2018). We made Figure 2, and Supplementary Figures A7 – A8, using the *MCMCvis* package (Youngflesh, 2018).

Results

The dry weight average concentration of fecal GCs across samples was 95.88 $\pm$ SD 31.04 ng/g, with minimum 0.01 ng/g and maximum 253 ng/g. We included time series graphs of individual study subjects' concentrations in Supplementary Figure A5, as there is a call for information on the repeatability of wild individuals' GC levels in the literature (Cockrem, 2013; Taff *et al.*, 2018).

The top model following DIC selection (Supplementary Table A5) included the covariates of adult caregivers, age mates, number of samples, with non-natal group, lactating, mean NDVI and NDVI standard deviation (Table 3.1, Figure 3.2). Lactating was the only covariate for which the 95% confidence interval overlapped 0 (Figure 3.2), and NDVI standard deviation was the only covariate that showed a positive correlation with GC levels. NDVI standard deviation followed by mean NDVI showed the strongest magnitude correlations (Table

3.1, Figures 3.2-3.3). The negative coefficient value for non-natal group also depicted a strong relationship. Then, in order of magnitude from largest to smallest, lactating, number of samples, age mates and adult caregivers negatively correlated with GCs. The estimated coefficients for these four covariates, especially the latter two, were similar (Table 3.1, Figure 3.2). Strongylid FECs dropped out of the model run with fewer samples (Supplementary Table A5), suggesting no correlation.

Table 3.1: Top model results.

Coefficient	Covariate	Estimate	95% CI lower	95% CI upper
β_1	adult caregivers	-0.16	-0.26	-0.06
β_2	age mates	-0.17	-0.26	-0.07
β_3	number of samples	-0.18	-0.28	-0.08
β_5	with non-natal group	-0.42	-0.79	-0.05
γ_2	lactating	-0.15	-0.33	0.02
γ_5	mean NDVI	-0.89	-1.37	-0.41
γ_7	NDVI standard deviation	0.99	0.51	1.47

Posterior predictive check graphs comparing simulated data from the top model with the real data showed our model predicts what we observed (Supplementary Figure A6). Results from the second ranked model (Supplementary Table A5), which suggested a positive correlation between pregnancy and GC levels, are shown in Supplementary Table A6 and Supplementary Figure A7. Results from the model including strongylid FECs, for which the model DIC score was similar to that without FECs for the smaller sample set (Supplementary Table A5), are in Supplementary Table A7 and Supplementary Figure A8. (See also supplemental information.)

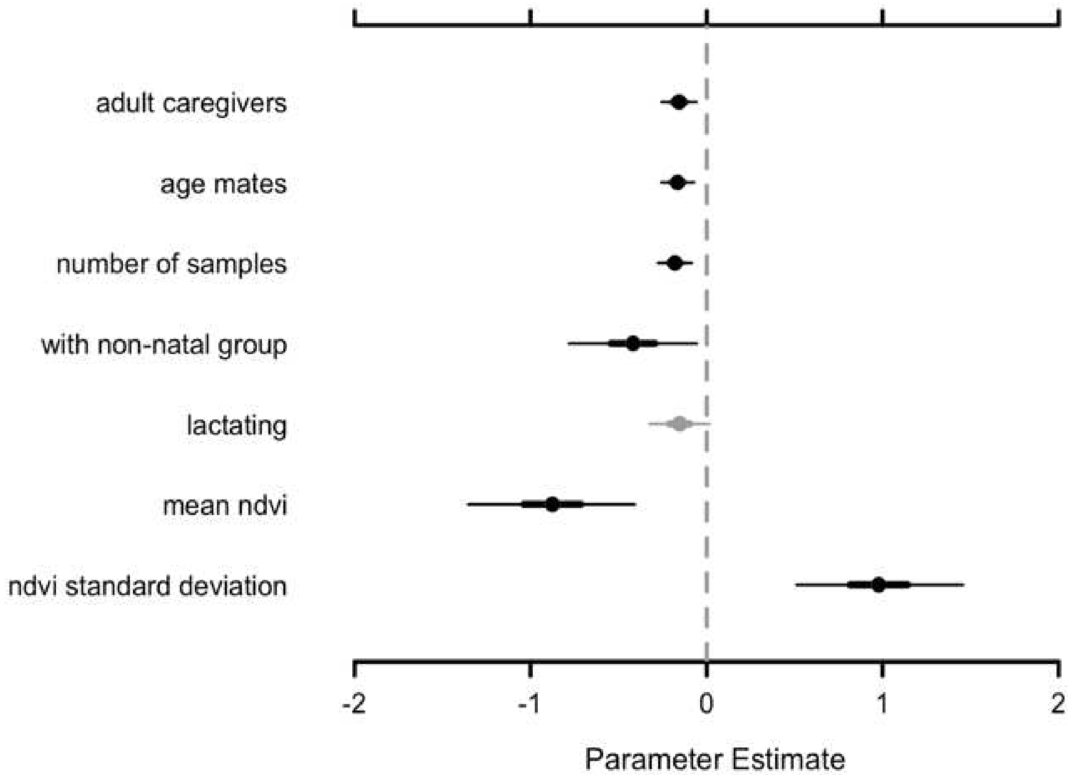


Figure 3.2: Results from the top model, with black denoting estimates whose 95% confidence interval did not overlap zero, and gray denoting estimates whose 50% confidence interval did not overlap zero.

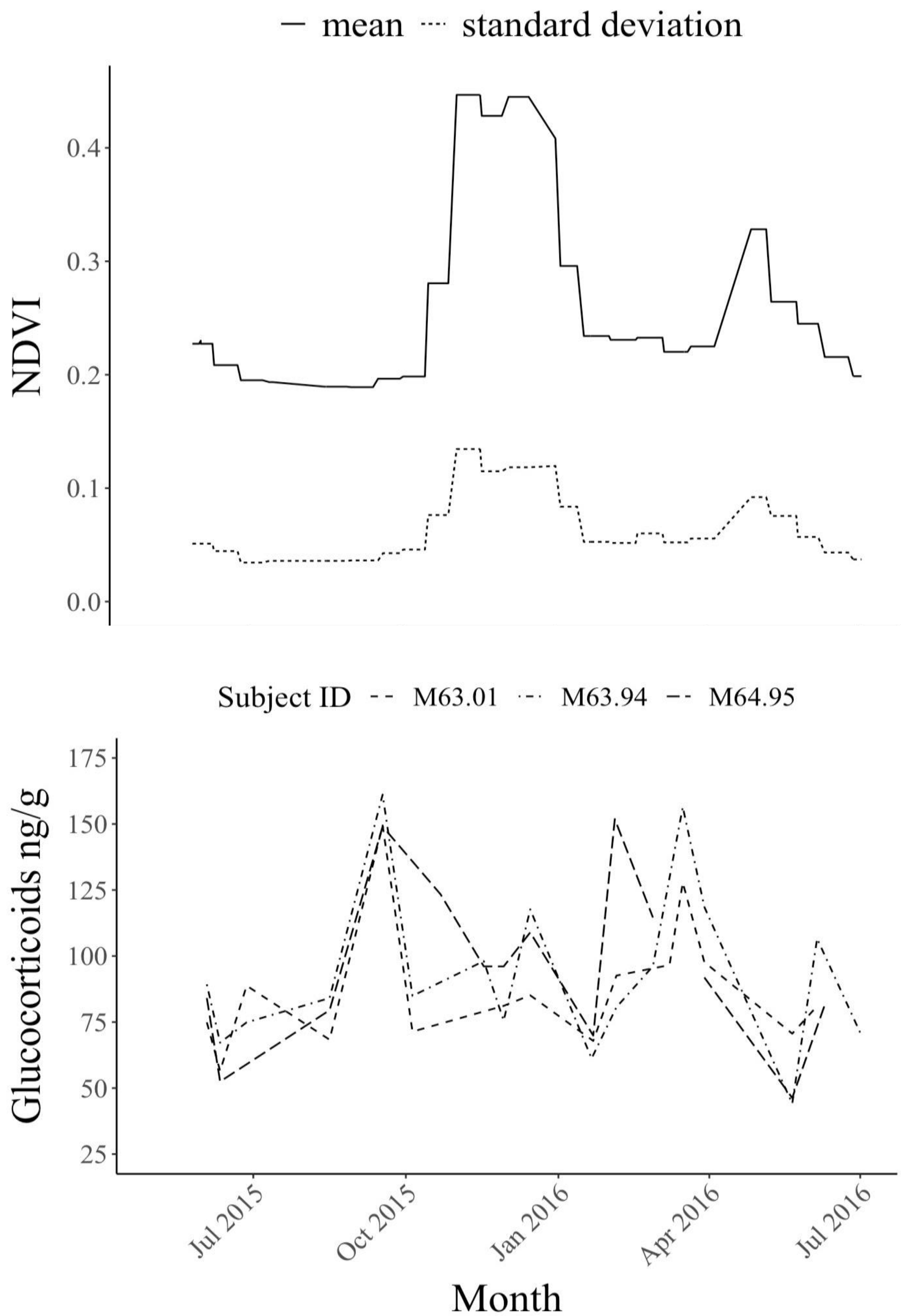


Figure 3.3: NDVI mean and standard deviation over the course of the study (top panel) above the glucocorticoid metabolite concentrations of three study subjects from the same family (bottom panel). Glucocorticoids fluctuated most in relation to changes in primary productivity.

Discussion

Our study was unique in investigating how maternal loss affects HPA axis activity in wild orphans of a long-lived mammal species. Our findings demonstrate that social context affects GC levels in African elephants. Baseline GC levels were lower for individuals in core groups with more multiparous adult females and age mates. Contrary to our expectation, we did not find evidence that surviving orphans had higher baseline GC levels. Elephant orphans suffer lower survival than nonorphans (Parker *et al.*, 2021), but our results indicate that for surviving orphans social buffering by family members may stymie extended increases in GC secretion. Goldenberg *et al.* (2016) found that orphan daughters use knowledge of their mother's relationships to maintain their position in the social network following her death, indicating the importance of social connections. These same bonds seem important to preventing harmful physiological effects of higher GC levels (Sapolsky, 2004).

Surprisingly, orphans away from their natal group, of which a majority came from families totally fragmented by poaching with no adults left, demonstrated lower average GC levels than nonorphans and orphans remaining with their family (Table 3.1, Figure 3.3). Given the challenges experienced by these orphans, including higher levels of aggression from other individuals (Goldenberg and Wittemyer, 2018), we surmised they would be the most stressed. Although increased secretion of GCs is traditionally equated with greater stress, physiology of the stress response is complicated and the HPA axis can exhibit either hyper- or hypo-secretion of GCs depending on the type and duration of a stressor (Heim *et al.*, 2000; Sapolsky *et al.*, 2000; Dickens and Romero, 2013; Ma *et al.*, 2018). Long-term social stressors, especially those whose onset is during developmental stages, can cause prolonged hypersecretion of GCs that eventually down-regulate HPA axis activity. This results in sustained lower baseline GC levels, a phenomenon termed hypocortisolism (Heim *et al.*, 2000; Gunnar and Vazquez, 2001; Ma *et al.*, 2018; Perry *et al.*, 2019), which could explain the lower levels in non-natal orphans. In the absence of social buffering, downregulation of the HPA axis may be an adaptive response, preventing harmful effects of consistently elevated GC levels (Blas *et al.*, 2007; Boonstra, 2013). However, hypocortisolism has also been associated with physiological problems such as autoimmunity, depression and excessive fatigue in humans (Fries *et al.*, 2005). A study in another cognitively advanced mammal found that maternal loss resulted in hypocortisolism; captive rhesus monkeys (*Macatta mulatta*) separated from their mothers at birth had significantly lower basal cortisol levels compared to controls three years following separation (Feng *et al.*, 2011). Assuming social buffering from family members lowers GCs of orphans after an initial rise, hypocortisolism in non-natal elephant orphans is a plausible explanation for our results.

Although we are unaware of other orphan/nonorphan studies in wildlife involving GC levels, in humans non-parental social buffering seems to alleviate negative effects associated with the loss of parents and hypocortisolism. AIDS-orphaned children in South Africa who perceived a high degree of social support from siblings, caretakers, friends and others were less likely than their peers to develop post-traumatic stress disorder, a common symptom of which is hypocortisolism (Heim *et al.*, 2000; Cluver *et al.*, 2009; González Ramírez *et al.*, 2020). Our findings concerning social context and GC levels in wild elephant orphans are therefore in line with findings in humans.

Basic survival needs are recognized as the primary regulators of the stress response (Sapolsky *et al.*, 2000; Boonstra, 2013). We designed this study to assess the effect of social factors on GC levels, but it was clear that ecological factors related to resource availability had the strongest effect (Table 3.1, Figures 3.2-3.3). GC levels were lower when mean NDVI was higher and vice versa, indicating that when food was readily available the study subjects' GC secretion was lower and when food was of lower quality their GC secretion was higher.. Conversely, GC levels were higher when NDVI standard deviation was high, during seasonal transitions with stochastic rainfall when food was distributed unpredictably across the landscape. We suspect the higher GC levels were related to greater challenges of locating high value resources (Bastille-Rousseau *et al.*, 2020).

We thought pregnant and/or lactating elephants would have higher GC levels given the energetically expensive nature of elephant reproduction (Laws, 1969). Previous studies have also found stage of gestation correlates positively with GC levels in African elephants (Foley *et al.*, 2001) and lactation correlates positively with GC levels in captive Asian elephants (*Elephas maximus*) (Glaeser *et al.*, 2020). In this study, pregnancy showed no reliable correlation with GC levels (but see Supplementary Table A6 and Supplementary Figure A7), perhaps due to our course 0/1 categorization that did not incorporate stage of gestation. Moreover, lactating elephants had lower GC levels (Table 3.1, Figure 3.3). This may be because lactating females release more oxytocin, a hormone that inhibits HPA axis activity and lowers GC secretion (DeVries, 2002; DeVries *et al.*, 2003; Reeder and Kramer, 2005). Interestingly, demographic analysis suggests females with dependent calves survive better (Wittemyer *et al.*, 2021), which could relate to oxytocin's effect on GC secretion. Oxytocin may further be the mechanism by which social buffering attenuates GC secretion; affiliative physical contact has been documented to release oxytocin in contexts unrelated to nursing and reproduction (DeVries *et al.*, 2003).

Regarding conservation, our results are hopeful for elephant populations that still contain functional family units. They suggest orphaning does not have lasting effects on the HPA axis of surviving African elephant orphans unless they disperse and lack the support of their natal group.

The level of poaching in the Samburu population was not high enough to destroy the majority of core groups and most orphans stayed with their family. Where heavier poaching has destroyed a greater number of family units, non-natal orphans would be more common. If non-natal orphans tend to develop hypocortisolism, there exists a mechanism for long-lived, residual effects of poaching beyond reduced elephant numbers and reduced orphan survival (Parker *et al.*, 2021; Wittemyer *et al.*, 2021) in some populations. Concerning management, evidence that social support can compensate for maternal loss is useful to caring for orphan elephants brought into captivity. Providing age mates and maintaining core groups of bonded orphans may reduce stress associated with captivity (Brown *et al.*, 2019), and releasing bonded groups together could ease their transition back into the wild (Goldenberg *et al.*, 2019).

Although our study was robust in the use of longitudinal sampling from well-known subjects of a long-term monitoring project, we could not sample evenly from all subjects (Figure 3.1D). This may have affected results, particularly given the number of samples we collected from an individual negatively correlated with her average GC levels (Table 3.1, Figure 3.3). We do not know the reason for this correlation, but we collected fewer samples from non-natal orphans and still found they had lower levels than more heavily sampled individuals (Figure 3.1D). Additionally, the sample size of orphan subjects who had left their natal family was small (n = 5, Figure 3.1A), and they tended to be in contexts with fewer adults and age mates (Figure 3.1 B-C). We could not remedy this because, as mentioned above, few orphans in the study system left their natal groups (Goldenberg and Wittemyer, 2018).

While not possible in our study, it would be valuable to sample from wild elephant orphans immediately following their mother's death to assess if there is an initial increase in their GC levels. Subsequent longitudinal sampling would then show how orphan GC levels progress and if negative feedback causes the lower levels observed in non-natal orphans. Extended research is also needed to investigate whether there are long-term fitness effects associated with our findings. Importantly, we cannot equate altered GC levels with reduced fitness (Dantzer *et al.*, 2014; Kaisin *et al.*, 2020); non-natal orphans in this study survived the duration of sampling, despite orphans having a lower survival probability in general (Parker *et al.*, 2021).

This study highlighted that non-parental familial relationships likely ameliorate maternal loss for surviving African elephant orphans in Samburu, Kenya. This amelioration may occurr over time, because we sampled from orphans at least two years following their mother's death. Our results are relevant to conserving elephants and potentially other highly social species. We recommend similar research in more heavily poached elephant populations, and in other wild mammal populations.

References

Banerjee SB, Arterbery AS, Fergus DJ and Adkins-Regan E (2012) Deprivation of maternal care has long-lasting consequences for the hypothalamic-pituitary-adrenal axis of zebra finches. *Proceedings of the Royal Society B: Biological Sciences* **279** 759–766. doi:10.1098/rspb.2011.1265

Bastille-Rousseau G, Wall J, Douglas-Hamilton I, Lesowapir B, Loloju B, Mwangi N and Wittemyer G (2020) Landscape-scale habitat response of African elephants shows strong selection for foraging opportunities in a human dominated ecosystem. *Ecography* **43** 149–160. doi:10.1111/ecog.04240

Blas J, Bortolotti GR, Tella JL, Baos R and Marchant TA (2007) Stress response during development predicts fitness in a wild, long lived vertebrate. *Proceedings of the National Academy of Sciences of the United States of America* **104** 8880–8884. doi:10.1073/pnas.0700232104

Boonstra R (2013) Reality as the leading cause of stress: Rethinking the impact of chronic stress in nature. *Functional Ecology* **27** 11–23. doi:10.1111/1365-2435.12008

Brooks SP and Gelman A (1998) General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics* **7** 434–455. doi:10.1080/10618600.1998.10474787

Brown JL, Kersey DC, Freeman EW and Wagener T (2010) Assessment of diurnal urinary cortisol excretion in Asian and African elephants using different endocrine methods. *Zoo Biology* **29** 274–283. doi:10.1002/zoo.20268

Brown JL, Carlstead K, Bray JD, Dickey D, Farin C and Heugten KA van (2019) Individual and environmental risk factors associated with fecal glucocorticoid metabolite concentrations in zoo-housed Asian and African elephants. *PLoS ONE* **14** 1–18. doi:10.1371/journal.pone.0217326

Caldji C, Diorio J and Meaney MJ (2000) Variations in maternal care in infancy regulate the development of stress reactivity. *Biological Psychiatry* **48** 1164–1174. doi:10.1016/S0006-3223(00)01084-2

Cluver L, Fincham DS and Seedat S (2009) Posttraumatic stress in AIDS-orphaned children exposed to high levels of trauma: The protective role of perceived social support. *Journal of Traumatic Stress* **22** 106–112. doi:10.1002/jts.20396

Cockrem JF (2013) Individual variation in glucocorticoid stress responses in animals. *General and Comparative Endocrinology* **181** 45–58. doi:10.1016/j.ygcen.2012.11.025

Dantzer B, Fletcher QE, Boonstra R and Sheriff MJ (2014) Measures of physiological stress: A transparent or opaque window into the status, management and conservation of species? *Conservation Physiology* **2** 1–18. doi:10.1093/conphys/cou023

DeVries AC (2002) Interaction among social environment, the hypothalamic-pituitary-adrenal axis, and behavior. *Hormones and Behavior* **41** 405–413. doi:10.1006/hbeh.2002.1780

DeVries AC, Glasper ER and Detillion CE (2003) Social modulation of stress responses. *Physiology and Behavior* **79** 399–407. doi:10.1016/S0031-9384(03)00152-5

Dickens MJ and Romero LM (2013) A consensus endocrine profile for chronically stressed wild animals does not exist. *General and Comparative Endocrinology* **191** 177–189. doi:10.1016/j.ygcen.2013.06.014

Douglas-Hamilton I, Bhalla S, Wittemyer G and Vollrath F (2006) Behavioural reactions of elephants towards a dying and deceased matriarch. *Applied Animal Behaviour Science* **100** 87–102.

Feng X, Wang L, Yang S, Qin D, Wang J, Li C, Lv L, Ma Y and Hu X (2011) Maternal separation produces lasting changes in cortisol and behavior in rhesus monkeys. *Proceedings of the National Academy of Sciences of the United States of America* **108** 14312–14317. doi:10.1073/pnas.1010943108

Foley CAH, Papageorge S and Wasser SK (2001) Noninvasive stress and reproductive measures of social and ecological pressures in free-ranging African elephants. *Conservation Biology* **15** 1134–1142. doi:10.1046/j.1523-1739.2001.0150041134.x

Fries E, Hesse J, Hellhammer J and Hellhammer DH (2005) A new view on hypocortisolism. *Psychoneuroendocrinology* **30** 1010–1016. doi:10.1016/j.psyneuen.2005.04.006

Gabry J and Mahr T (2020) bayesplot: Plotting for Bayesian Models. R package version 1.7.2, <https://m-stan.org/bayesplot>

Ganswindt A, Rasmussen HB, Heistermann M and Hodges JK (2005) The sexually active states of free-ranging male African elephants (Loxodonta africana): defining musth and non-musth using endocrinology, physical signals, and behavior. *Hormones and Behavior* **47** 83–91. doi:10.1016/j.yhbeh.2004.09.002

Gelman A and Rubin DB (1992) Inference from iterative simulation using multiple sequences. *Statistical Science* **7** 457–511.

Gibbons L, Jacobs DE, Fox MT and Hansen J (2004) The RVC/FAO guide to veterinary diagnostic parasitology. McMaster egg-counting technique. Available at http://www.rvc.ac.uk/review/Parasitology/EggCount/Purpose.htm (accessed March 2015)

Gjerstad JK, Lightman SL and Spiga F (2018) Role of glucocorticoid negative feedback in the regulation of HPA axis pulsatility. *Stress* **21** 403–416. doi:10.1080/10253890.2018.1470238

Glaeser SS, Edwards KL, Wielebnowski N and Brown JL (2020) Effects of physiological changes and social life events on adrenal glucocorticoid activity in female zoo-housed Asian elephants (Elephas maximus). *PLoS ONE* **15** 1–36. doi:10.1371/journal.pone.0241910

Gobush KS, Mutayoba BM and Wasser SK (2008) Long-Term Impacts of Poaching on Relatedness, Stress Physiology, and Reproductive Output of Adult Female African Elephants. *Conservation Biology* **22** 1590–1599. doi:10.1111/j.1523-1739.2008.01035.x

Gobush KS, Edwards CT., Balfour D, Wittemyer G, Maisels F and Taylor RD (2021) *Loxodonta africana* (African Savanna Elephant). In *The IUCN Red List of Threatened Species 2021*, p e.T181008073A181022663. doi:10.2305/IUCN.UK.2021-1.RLTS.T181008073A181022663.en

Goldenberg SZ and Wittemyer G (2017) Orphaned female elephant social bonds reflect lack of access to mature adults. *Scientific Reports* **7** 14408. doi:10.1038/s41598-017-14712-2

Goldenberg SZ and Wittemyer G (2018) Orphaning and natal group dispersal are associated with social costs in female elephants. *Animal Behaviour* **143** 1–8. doi:10.1016/j.anbehav.2018.07.002

Goldenberg SZ, Douglas-Hamilton I and Wittemyer G (2016) Vertical Transmission of Social Roles Drives Resilience to Poaching in Elephant Networks. *Current Biology* **26** 75–79. doi:10.1016/j.cub.2015.11.005

Goldenberg SZ, Owen MA, Brown JL, Wittemyer G, Oo ZM and Leimgruber P (2019) Increasing conservation translocation success by building social functionality in released populations. *Global Ecology and Conservation* **18**. doi:10.1016/j.gecco.2019.e00604

González Ramírez C, Villavicencio Queijeiro A, Jiménez Morales S, Bárcenas López D,

Hidalgo Miranda A, Ruiz Chow A, Tellez Cárdenas L and Guardado Estrada M (2020) The NR3C1 gene expression is a potential surrogate biomarker for risk and diagnosis of posttraumatic stress disorder. *Psychiatry Research* **284** 112797. doi:10.1016/j.psychres.2020.112797

Gunnar MR and Vazquez DM (2001) Low cortisol and a flattening of expected daytime rhythm: Potential indices of risk in human development. *Development and Psychopathology* **13** 515–538. doi:10.1017/S0954579401003066

Heim C, Ehlert U and Hellhammer DH (2000) The potential role of hypocortisolism in the pathophysiology of stress-related bodily disorders. *Psychoneuroendocrinology* **25** 1–35.

Hennessy MB, Nigh CK, Sims ML and Long SJ (1995) Plasma cortisol and vocalization responses of postweaning age guinea pigs to maternal and sibling separation: Evidence for filial attachment after weaning. *Developmental Psychobiology* **28** 103–115. doi:10.1002/dev.420280204

Hennessy MB, Kaiser S and Sachser N (2009) Social buffering of the stress response: Diversity, mechanisms, and functions. *Frontiers in Neuroendocrinology* **30** 470–482. doi:10.1016/j.yfrne.2009.06.001

Hooten MB and Hobbs NT (2015) A guide to Bayesian model selection for ecologists. *Ecological Monographs* **85** 3–28.

Justice CO, Vermote E, Townshend JRG, Defries R, Roy DP, Hall DK, Salomonson V V., Privette JL, Riggs G, Strahler A *et al.* (1998) The moderate resolution imaging spectroradiometer (MODIS): Land remote sensing for global change research. *IEEE Transactions on Geoscience and Remote Sensing* **36** 1228–1249. doi:10.1109/36.701075

Kaisin O, Fuzessy L, Poncin P, Brotcorne F and Culot L (2020) A meta-analysis of anthropogenic impacts on physiological stress in wild primates. *Conservation Biology* **0** 1–14. doi:10.1111/cobi.13656

Lafferty DJR, Zimova M, Clontz L, Hackländer K and Mills LS (2019) Noninvasive measures of physiological stress are confounded by exposure. *Scientific Reports* **9** 1–6. doi:10.1038/s41598-019-55715-5

Laws RM (1969) Aspects of reproduction in the African elephant (Loxodonta africana). *Journal of Reproduction and Fertility Supplement* **6** 193–217.

Lee PC (1987) Allomothering among African elephants. *Animal Behaviour* **35** 278–291. doi:10.1016/S0003-3472(87)80234-8

Liu D, Diorio J, Tannenbaum B, Caldji C, Francis D, Freedman A, Sharma S, Pearson D, Plotsky PM and Meaney MJ (1997) Maternal Care, hippocampal glucocorticoid receptors, and hypothalamic-pituitary-adrenal responses to stress. *The Science of Mental Health: Stress and the Brain* **9** 75–78. doi:10.7551/mitpress/3077.003.0053

Ma D, Serbin LA and Stack DM (2018) How children's anxiety symptoms impact the functioning of the hypothalamus–pituitary–adrenal axis over time: A cross-lagged panel approach using hierarchical linear modeling. *Development and Psychopathology* **31** 1–15. doi:10.1017/S0954579417001870

McCormick SD and Romero LM (2017) Conservation endocrinology. *BioScience* **67** 429–442. doi:10.1093/biosci/bix026

Moss C (1988) *Elephant Memories: Thirteen Years in the Life of an Elephant Family*. Chicago: The University of Chicago Press.

Novak MA, Hamel AF, Kelly BJ, Dettmer AM and Meyer JS (2013) Stress, the HPA axis, and nonhuman primate well-being: A review. *Applied Animal Behaviour Science* **143** 135–

149. doi:10.1016/j.applanim.2012.10.012

O'Dwyer K, Dargent F, Forbes MR and Koprivnikar J (2020) Parasite infection leads to widespread glucocorticoid hormone increases in vertebrate hosts: A meta-analysis. *Journal of Animal Ecology* **89** 519–529. doi:10.1111/1365-2656.13123

Oduor S, Brown J, Macharia GM, Boisseau N, Murray S and Obade P (2020) Differing physiological and behavioral responses to anthropogenic factors between resident and non-resident African elephants at Mpala Ranch, Laikipia County, Kenya. *PeerJ* **8**. doi:10.7717/peerj.10010

Parker JM, Goldenberg SZ, Letitiya D and Wittemyer G (2020) Strongylid infection varies with age, sex, movement and social factors in wild African elephants. *Parasitology* **147** 348–359. doi:10.1017/S0031182019001653

Parker JM, Webb CT, Daballen D, Goldenberg SZ, Lepirei J, Letitiya D, Lolchuragi D, Leadismo C, Douglas-Hamilton I and Wittemyer G (In press 2021) Poaching of African elephants indirectly decreases population growth through lowered orphan survival. *Current Biology*.

Perry RE, Rincón-Cortés M, Braren SH, Brandes-Aitken AN, Opendak M, Pollonini G, Chopra D, Raver CC, Alberini CM, Blair C *et al.* (2019) Corticosterone administration targeting a hypo-reactive HPA axis rescues a socially-avoidant phenotype in scarcity-adversity reared rats. *Developmental Cognitive Neuroscience* **40**. doi:10.1016/j.dcn.2019.100716

Plummer M (2019) rjags: Bayesian graphical models using MCMC. R package version 4-10. <https://CRAN.R-project.org/package=rjags>

R Core Team (2018) *A language and environment for statistical computing*. Vienna, Austria.

<https://www.R-project.org/>

Reeder DAM and Kramer KM (2005) Stress in free-ranging mammals: Integrating physiology, ecology, and natural history. *Journal of Mammalogy* **86** 225–235. doi:10.1644/BHE-003.1

Rstudio Team (2016) *RStudio: Integrated development for R*. Boston, MA. <http://www.rstudio.com/>

Sapolsky RM (2004) *Why Zebras Don't Get Ulcers*. New York: Henry Holt and Company, LLC.

Sapolsky RM, Romero LM and Munck AU (2000) How do glucocorticoids influence stress responses? Integrating permissive, suppressive, stimulatory, and preparative actions. *Endocrine Reviews* **21** 55–89. doi:10.1210/er.21.1.55

Spiegelhalter DJ, Best NG, Carlin BP and Van Der Linde A (2002) Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society. Series B: Statistical Methodology* **64** 583–616. doi:10.1111/1467-9868.00353

Spiga F, Walker JJ, Terry JR and Lightman SL (2014) HPA axis-rhythms. *Comprehensive Physiology* **4** 1273–1298. doi:10.1002/cphy.c140003

Stanton ME, Patterson JM and Levine S (1985) Social influences on conditioned cortisol secretion in the squirrel monkey. *Psychoneuroendocrinology* **10** 125–134.

Taff CC, Schoenle LA and Vitousek MN (2018) The repeatability of glucocorticoids: A review and meta-analysis. *General and Comparative Endocrinology* **260** 136–145. doi:10.1016/j.ygcen.2018.01.011

Watson R, Munro C, Edwards KL, Norton V, Brown JL and Walker SL (2013) Development of a versatile enzyme immunoassay for non-invasive assessment of glucocorticoid metabolites in a diversity of taxonomic species. *General and Comparative*

Endocrinology **186** 16–24. doi:10.1016/j.ygcen.2013.02.001

Wickham H (2016) *ggplot2: Elegant graphics for data analysis.*New York: Springer-Verlag.

Wiener SG, Johnson DF and Levine S (1987) Influence of postnatal rearing conditions on the response of squirrel monkey infants to brief perturbations in mother-infant relationships. *Physiology and Behavior* **39** 21–26. doi:10.1016/0031-9384(87)90339-8

Wittemyer G (2001) The elephant population of Samburu and Buffalo Springs National Reserves, Kenya. *African Journal of Ecology* **39** 357–369. doi:10.1046/j.1365-2028.2001.00324.x

Wittemyer G, Getz WM, Vollrath F and Douglas-Hamilton I (2007) Social dominance, seasonal movements, and spatial segregation in African elephants: A contribution to conservation behavior. *Behavioral Ecology and Sociobiology* **61** 1919–1931. doi:10.1007/s00265-007-0432-0

Wittemyer G, Okello JBA, Rasmussen HB, Arctander P, Nyakaana S, Douglas-Hamilton I and Siegismund HR (2009) Where sociality and relatedness diverge: the genetic basis for hierarchical social organization in African elephants. *Proceedings of the Royal Society B: Biological Sciences* **276** 3513–3521. doi:10.1098/rspb.2009.0941

Wittemyer G, Daballen D and Douglas-Hamilton I (2013) Comparative Demography of an At-Risk African Elephant Population. *PLoS ONE* **8**. doi:10.1371/journal.pone.0053726

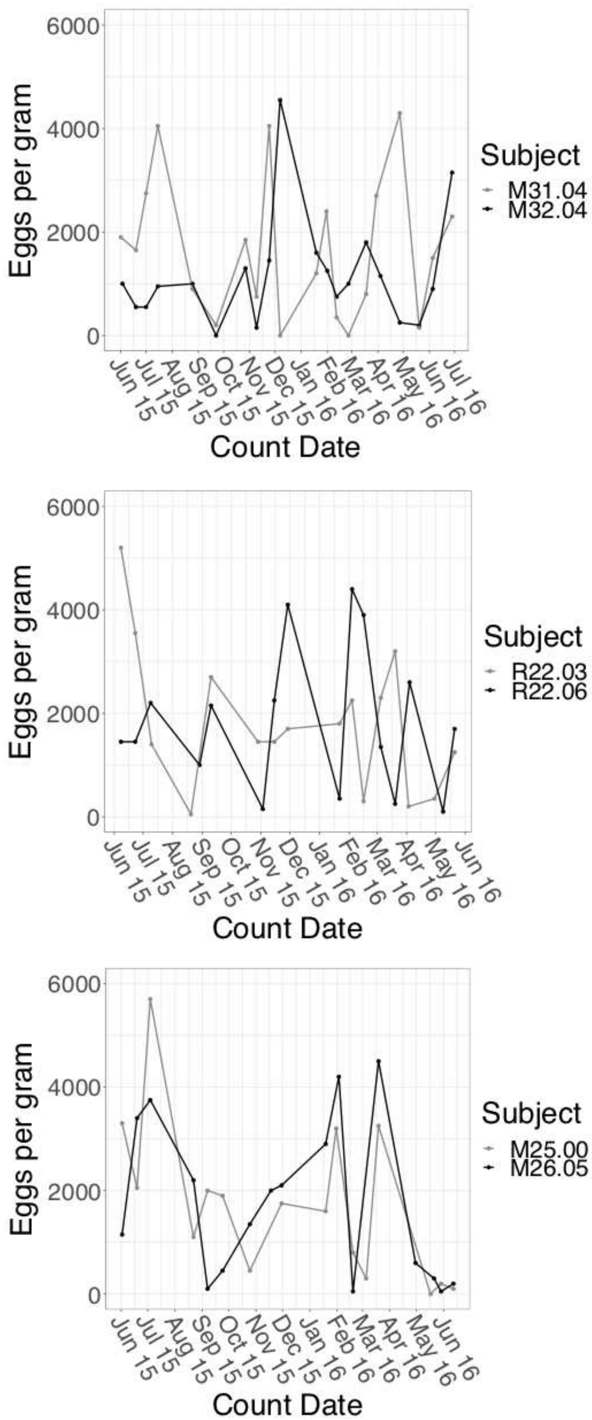
Wittemyer G, Northrup JM, Blanc J, Douglas-Hamilton I, Omondi P and Burnham KP (2014) Illegal killing for ivory drives global decline in African elephants. *Proceedings of the National Academy of Sciences* **111** 13117–13121. doi:10.1073/pnas.1403984111

Wittemyer G, Daballen D and Douglas-Hamilton I (In press 2021) Differential influence of human impacts on age-specific demography underpin trends in an African elephant population. *Ecosphere*.

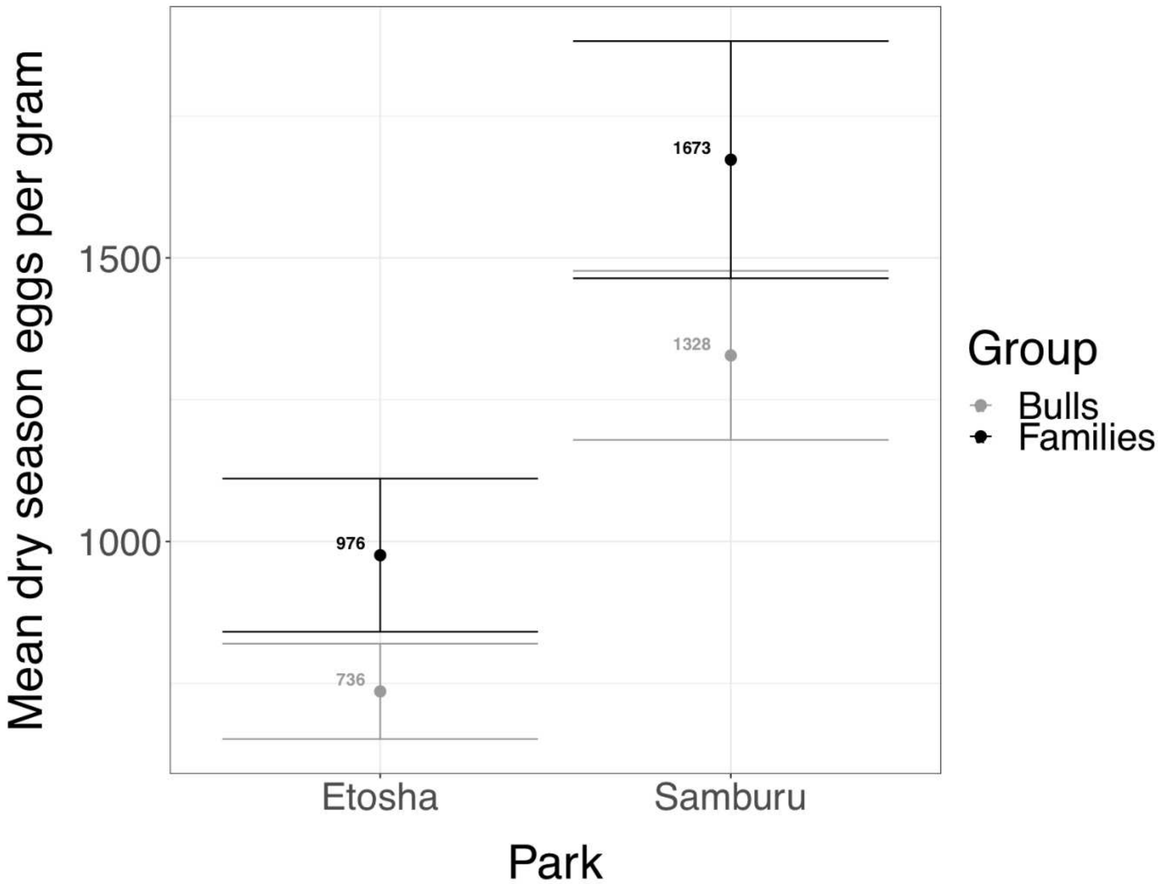
Young C, Majolo B, Heistermann M, Schülke O and Ostner J (2014) Responses to social and environmental stress are attenuated by strong male bonds in wild macaques. *Proceedings of the National Academy of Sciences of the United States of America* **111** 18195–18200. doi:10.1073/pnas.1411450111

Youngflesh C (2018) MCMCvis: Tools to Visualize, Manipulate, and Summarize MCMC Output. *Journal of Open Source Software* **3** 640. doi:10.21105/joss.00640

APPENDIX 1: Supplementary materials for Chapter 1



Supplementary Figure A1: Repeated measures strongylid eggs per gram of dung counts for two females each of three families, showing the prevailing oscillatory pattern of sample counts over time for a single individual



Supplementary Figure A2: Comparison of strongylid eggs per gram of dung counts for Etosha National Park of Namibia as reported by Thurber *et al*. (2011), and the Samburu elephant population of Kenya as reported in this publication. Means reported in this figure for the Samburu population are only for samples collected during the dry season, since the Etosha study was conducted only during dry seasons. Bulls sampled in Etosha were older than bulls sampled in Samburu, who were not yet completely dispersed.

APPENDIX 2: Supplemental information for Chapter 2

Projection matrix

Notably, the three orphaning probabilities within the matrix, from 0-2 years into orphan 0-2 years (“Z_{02}”), 3-8 years into orphan 3-8 years (“Z_{38}”), and 9-18 years into orphan 9-18 years (“Z_{918}”), are distinguished from other transition rates because they are multiplied by the survival rate of the stage class which they are entering as opposed to the previous stage class (Supplementary Figure A3). This is because these orphaning transitions occur at any time during the year, as opposed to the other “pulsed” age-based transitions, and we wanted to properly capture the death of orphan individuals who were both orphaned and died during the same year.

Orphan calves under the age of 2 have never survived within the Samburu population (Wittemyer *et al.*, 2013). The lack of an outlet from the orphan 0-2 class made our projection matrix *reducible*, meaning it contained *at least one stage that cannot contribute, by any developmental path, to some other stage or stages* (Caswell, 2001). There are concerns about reducible matrices and their use in sensitivity analyses (Caswell, 2019). We tested whether the reducibility of our matrix was problematic by assigning the 0-2 orphan class stage a very low survival rate (see beta_parameters_irr of Appendix 3), such that the matrix was irreducible, and re-running the described sensitivity analysis. The results were nearly identical to our primary model results, indicating reducibility is not a cause for concern in this instance.

Correlation

The correlations in our model between adult survival and orphan survival draws were lower than observed in the data (see Appendix 4). We originally attempted to correlate variables using the method of Iman and Conover (1982), but the data-derived correlation matrix was not positive definite, and correcting it to be so gave correlations further from the data-derived correlations than the conditional method we devised (see LHS_draws of Appendix 3).

Supplementary Table A1: Average, minimum and maximum annual sample sizes for each stage class over the 19 study years of 1999 – 2017. Apart from the 0 – 2 orphan stage class in which all individuals died (total n = 14), we excluded years with <5 individuals in calculations, therefore the year 1999 was discounted for the 3 – 8 orphan stage class (1 individual), and the years 1999 and 2000 were discounted for the 9 – 18 orphan stage class (0 and 1 individual, respectively).

Stage class	**Average annual sample size**	**Minimum n**	**Maximum n**
0 – 2 nonorphan	38.21	21	60
0 – 2 orphan	0.74 (total n = 14)	0	2
3 – 8 nonorphan	80.26	59	105
3 – 8 orphan	10.61	5	23
9 – 18 nonorphan	79.52	50	103
9 – 18 orphan	35.59	5	71
19 – 35	66.26	46	83
> 35	34.79	20	48

Supplementary Table A2: Linear regression coefficient estimates, arranged from greatest absolute value to least, for (A) the overall model, (B) the period of less poaching, and (C) the period of more poaching. Negative coefficients are shaded gray. The letter F and G signify fertility, S and V survival, and T and U age-based transitions for nonorphans and orphans, respectively. Z signifies transition-into-orphan probabilities. The adjusted R^2 value for each model is included.

A

Vital rate	Coefficient estimate	p-value	Adjusted R^2
F 19-35	0.382	<0.001	0.826
S 3-8	0.248	<0.001	
F >35	0.219	<0.001	
Z 3-8 orphaning	-0.213	<0.001	
F 9-18	0.208	<0.001	
S 19-35	0.199	<0.001	
T 3-8 into 9-18	0.166	<0.001	
V orphan 9-18	0.157	<0.001	
G orphan 9-18	0.153	<0.001	
S 0-2	0.150	<0.001	
S 9-18	0.149	<0.001	
T 0-2 into 3-8	0.144	<0.001	
Z 0-2 orphaning	-0.118	<0.001	
S >35	0.114	<0.001	
V orphan 3-8	0.076	<0.001	
T 19-35 into >35	-0.074	<0.001	
Z 9-18 orphaning	-0.059	<0.001	
U orphan 3-8 into orphan 9-18	0.035	<0.001	
T 9-18 into 19-35	-0.025	<0.001	
U orphan 9-18 into 19-35	-0.023	<0.001	

B

Vital rate	Coefficient estimate	p-value	Adjusted R^2
F 19-35	0.409	<0.001	0.853
F 9-18	0.350	<0.001	
F >35	0.349	<0.001	
T 3-8 into 9-18	0.266	<0.001	
S 19-35	0.177	<0.001	
S 9-18	0.170	<0.001	
Z 3-8 orphaning	-0.167	<0.001	
S >35	0.154	<0.001	
G orphan 9-18	0.138	<0.001	
V orphan 9-18	0.134	<0.001	
T 0-2 into 3-8	0.097	<0.001	
S 0-2	0.089	<0.001	
S 3-8	0.083	<0.001	
V orphan 3-8	0.072	<0.001	
T 19-35 into >35	-0.065	<0.001	
Z 0-2 orphaning	-0.063	<0.001	
Z 9-18 orphaning	-0.057	<0.001	
U orphan 3-8 into orphan 9-18	0.038	<0.001	
T 9-18 into 19-35	-0.023	<0.001	
U orphan 9-18 into 19-35	-0.005	0.223	

C

Vital rate	Coefficient estimate	p-value	Adjusted R^2
F 19-35	0.419	<0.001	0.790
V orphan 9-18	0.367	<0.001	
S 19-35	0.286	<0.001	
S 3-8	0.274	<0.001	
S 0-2	0.210	<0.001	
G orphan 9-18	0.209	<0.001	
T 0-2 into 3-8	0.200	<0.001	
Z 3-8 orphaning	-0.113	<0.001	
V orphan 3-8	0.104	<0.001	
F >35	0.103	<0.001	
U orphan 9-18 into 19-35	-0.094	<0.001	
F 9-18	0.091	<0.001	
Z 0-2 orphaning	-0.089	<0.001	
T 3-8 into 9-18	0.072	<0.001	
T 19-35 into >35	-0.068	<0.001	
S >35	0.047	<0.001	
S 9-18	0.035	<0.001	
U orphan 3-8 into orphan 9-18	0.018	<0.001	
T 9-18 into 19-35	-0.016	<0.001	
Z 9-18 into orphan	0.006	0.620	

	Nonorphan 0-2	Orphan 0-2	Nonorphan 3-8	Orphan 3-8	Nonorphan 9-18	Orphan 9-18	19-35	>35
Nonorphan 0-2	S_{02} * $(1 – T_{02} – Z_{02})$	0	0	0	F_{918} * S_{918} * $(1 – T_{918})$	G_{918} * V_{918} * $(1 – U_{918})$	F_{1935} * S_{1935} * $(1 – T_{1935})$	$F_{>35}$ *$S_{>35}$
Orphan 0-2	Z_{02} * 0	0	0	0	0	0	0	0
Nonorphan 3-8	T_{02} * S_{02}	0	S_{38} * $(1 – T_{38} – Z_{38})$	0	0	0	0	0
Orphan 3-8	0	0	Z_{38} * V_{38}	V_{38} * $(1 – U_{38})$	0	0	0	0
Nonorphan 9-18	0	0	T_{38} * S_{38}	0	S_{918} * $(1 – T_{918} – Z_{918})$	0	0	0
Orphan 9-18	0	0	0	U_{38} * V_{38}	Z_{918} * V_{918}	V_{918} * $(1 – U_{918})$	0	0
19-35	0	0	0	0	T_{918} * S_{918}	U_{918} * V_{918}	S_{1935} * $(1 – T_{1935})$	0
>35	0	0	0	0	0	0	T_{1935} * S_{1935}	$S_{>35}$

abbreviation	corresponding vital rate
S_{02}	survival of nonorphan 0-2 stage class
T_{02}	transition from nonorphan 0-2 into nonorphan 3-8 stage class
Z_{02}	orphaning from nonorphan 0-2 into orphan 0-2 stage class
S_{38}	survival of nonorphan 3-8 stage class
T_{38}	transition from nonorphan 3-8 into nonorphan 9-18 stage class
U_{38}	transition from orphan 3-8 into orphan 9-18 stage class
Z_{38}	orphaning from nonorphan 3-8 into orphan 3-8 stage class
V_{38}	survival of 3-8 orphan stage class
S_{918}	survival of 9-18 nonorphan stage class
V_{918}	survival of orphan 9-18 stage class
T_{918}	transition from nonorphan 9-18 into 19-35 stage class
U_{918}	transition from orphan 9-18 into 19-35 stage class
Z_{918}	orphaning from nonorphan 9-18 stage class into orphan 9-18 stage class
F_{918}	fertility of nonorphan 9-18 stage class
G_{918}	fertility of orphan 9-18 stage class
S_{1935}	survival of 19-35 stage class
T_{1935}	transition from 19-35 into >35 stage class
F_{1935}	fertility of 19-35 stage class
$S_{>35}$	survival of >35 stage class
$F_{>35}$	fertility of >35 stage class

Supplementary Figure A3: Projection matrix corresponding to **A** in the equation **n**(t+1) = **An**(t), where **n**(t) is the population vector at time t, with a description of abbreviations.

Additional supplemental reference (not included in Chapter 2 primary references):

Iman, R.L., and Conover, W.J. (1982) A distribution-free approach to inducing rank correlation among input variables. *Communications in Statistics* **11** 311–334.

APPENDIX 3: MatLab Code for Chapter 2

beta_parameters

```
s02_a = 24.5182;
s02_b = 1.27207;

t02_38_a = 2.71247;
t02_38_b = 3.31588;

t02_orph_a = 3.09454;
t02_orph_b = 93.1073;

s38_a = 22.802;
s38_b = 0.831857;

s38orph_a = 16.6804;
s38orph_b = 2.71532;

t38_918_a = 4.14204;
t38_918_b = 26.9282;

t38orph_918orph_a = 3.93803;
t38orph_918orph_b = 8.77905;

t38_orph_a = 1.5701;
t38_orph_b = 29.1613;

s918_a = 37.0114;
s918_b = 1.29085;

s918orph_a = 31.0794;
s918orph_b = 2.1213;

t918_1935_a = 3.1007;
t918_1935_b = 35.8117;

t918orph_1935_a = 2.42803;
t918orph_1935_b = 42.3723;

t918_orph_a = 1.38622;
t918_orph_b = 33.3096;

f918_a = 3.46027;
```

```
f918_b = 38.8583;

f918orph_a = 3.00076;
f918orph_b = 29.4991;

s1935_a = 28.2788;
s1935_b = 1.59418;

t1935_36_a = 1.93196;
t1935_36_b = 38.1749;

f1935_a = 1.7622;
f1935_b = 13.6103;

s36_a = 13.2073;
s36_b = 1.41188;

f36_a = 1.55543;
f36_b = 10.5966;

%Creating AB matrix

AB = [s02_a, t02_38_a, t02_orph_a, s38_a, s38orph_a, t38_918_a, t38orph_918orph_a,
t38_orph_a, s918_a, s918orph_a, t918_1935_a, t918orph_1935_a, t918_orph_a, f918_a,
f918orph_a, s1935_a, t1935_36_a, f1935_a, s36_a,f36_a;

s02_b, t02_38_b,t02_orph_b, s38_b, s38orph_b, t38_918_b, t38orph_918orph_b, t38_orph_b,
s918_b, s918orph_b, t918_1935_b, t918orph_1935_b, t918_orph_b, f918_b, f918orph_b,
s1935_b, t1935_36_b, f1935_b, s36_b, f36_b];
```

beta_parameters_irr

```
s02_a = 24.5182;
s02_b = 1.27207;

t02_38_a = 2.71247;
t02_38_b = 3.31588;

t02_orph_a = 3.09454;
t02_orph_b = 93.1073;

s38_a = 22.802;
s38_b = 0.831857;

s38orph_a = 16.6804;
s38orph_b = 2.71532;

t38_918_a = 4.14204;
t38_918_b = 26.9282;

t38orph_918orph_a = 3.93803;
t38orph_918orph_b = 8.77905;

t38_orph_a = 1.5701;
t38_orph_b = 29.1613;

s918_a = 37.0114;
s918_b = 1.29085;

s918orph_a = 31.0794;
s918orph_b = 2.1213;

t918_1935_a = 3.1007;
t918_1935_b = 35.8117;

t918orph_1935_a = 2.42803;
t918orph_1935_b = 42.3723;

t918_orph_a = 1.38622;
t918_orph_b = 33.3096;

f918_a = 3.46027;
f918_b = 38.8583;

f918orph_a = 3.00076;
f918orph_b = 29.4991;
```

```
s1935_a = 28.2788;
s1935_b = 1.59418;

t1935_36_a = 1.93196;
t1935_36_b = 38.1749;

f1935_a = 1.7622;
f1935_b = 13.6103;

s36_a = 13.2073;
s36_b = 1.41188;

f36_a = 1.55543;
f36_b = 10.5966;

s02orph_a = 3.07984;
s02orph_b = 92.7687;

t02orph_38orph_a = 3.07984;
t02orph_38orph_b = 92.7687;

%Creating AB matrix

AB = [s02_a, t02_38_a, t02_orph_a, s38_a, s38orph_a, t38_918_a, t38orph_918orph_a,
t38_orph_a, s918_a, s918orph_a, t918_1935_a, t918orph_1935_a, t918_orph_a, f918_a,
f918orph_a, s1935_a, t1935_36_a, f1935_a, s36_a,f36_a, s02orph_a, t02orph_38orph_a;

s02_b, t02_38_b,t02_orph_b, s38_b, s38orph_b, t38_918_b, t38orph_918orph_b, t38_orph_b,
s918_b, s918orph_b, t918_1935_b, t918orph_1935_b, t918_orph_b, f918_b, f918orph_b,
s1935_b, t1935_36_b, f1935_b, s36_b, f36_b, s02orph_b, t02orph_38orph_b];
```

beta_parameters_less_poaching

s02_a = 76.1842;
s02_b = 2.38205;

t02_38_a = 6.91957;
t02_38_b = 7.95702;

t02_orph_a = 4.86214;
t02_orph_b = 180.865;

s38_a = 237.537;
s38_b = 2.87762;

s38orph_a = 18.8628;
s38orph_b = 3.41407;

t38_918_a = 3.78473;
t38_918_b = 23.6912;

t38orph_918orph_a = 3.4658;
t38orph_918orph_b = 8.13406;

t38_orph_a = 2.03016;
t38_orph_b = 52.5901;

s918_a = 88.1529;
s918_b = 1.69872;

s918orph_a = 32.6203;
s918orph_b = 1.96846;

t918_1935_a = 3.24676;
t918_1935_b = 43.9343;

t918orph_1935_a = 2.8387;
t918orph_1935_b = 44.5732;

t918_orph_a = 1.62985;
t918_orph_b = 64.3361;

f918_a = 4.00698;
f918_b = 44.5195;

f918orph_a = 2.9119;
f918orph_b = 27.2122;

```
s1935_a = 65.6318;
s1935_b = 2.27325;

t1935_36_a = 2.41606;
t1935_36_b = 39.3885;

f1935_a = 2.53765;
f1935_b = 19.9774;

s36_a = 37.1797;
s36_b = 2.2453;

f36_a = 1.77349;
f36_b = 12.1116;


%Creating AB matrix

AB = [s02_a, t02_38_a, t02_orph_a, s38_a, s38orph_a, t38_918_a, t38orph_918orph_a,
t38_orph_a, s918_a, s918orph_a, t918_1935_a, t918orph_1935_a, t918_orph_a, f918_a,
f918orph_a, s1935_a, t1935_36_a, f1935_a, s36_a,f36_a;

s02_b, t02_38_b,t02_orph_b, s38_b, s38orph_b, t38_918_b, t38orph_918orph_b, t38_orph_b,
s918_b, s918orph_b, t918_1935_b, t918orph_1935_b, t918_orph_b, f918_b, f918orph_b,
s1935_b, t1935_36_b, f1935_b, s36_b, f36_b];
```

beta_parameters_more_poaching

s02_a = 13.3371;
s02_b = 1.29779;

t02_38_a = 1.21956;
t02_38_b = 1.64668;

t02_orph_a = 2.70726;
t02_orph_b = 57.4361;

s38_a = 17.6144;
s38_b = 1.60847;

s38orph_a = 16.9513;
s38orph_b = 2.17811;

t38_918_a = 5.50189;
t38_918_b = 39.0182;

t38orph_918orph_a = 5.69341;
t38orph_918orph_b = 11.4505;

t38_orph_a = 1.85817;
t38_orph_b = 21.1782;

s918_a = 102.058;
s918_b = 7.19275;

s918orph_a = 34.6684;
s918orph_b = 2.8822;

t918_1935_a = 4.24712;
t918_1935_b = 36.9104;

t918orph_1935_a = 2.15997;
t918orph_1935_b = 47.1394;

t918_orph_a = 6.19263;
t918_orph_b = 78.4868;

f918_a = 2.68485;
f918_b = 30.8584;

f918orph_a = 3.31137;
f918orph_b = 35.9508;

```
s1935_a = 36.1795;
s1935_b = 3.84577;

t1935_36_a = 2.36697;
t1935_36_b = 84.5756;

f1935_a = 1.09079;
f1935_b = 8.10326;

s36_a = 15.3519;
s36_b = 3.3759;

f36_a = 1.23573;
f36_b = 8.37418;

%Creating AB matrix

AB = [s02_a, t02_38_a, t02_orph_a, s38_a, s38orph_a, t38_918_a, t38orph_918orph_a,
t38_orph_a, s918_a, s918orph_a, t918_1935_a, t918orph_1935_a, t918_orph_a, f918_a,
f918orph_a, s1935_a, t1935_36_a, f1935_a, s36_a,f36_a;

s02_b, t02_38_b,t02_orph_b, s38_b, s38orph_b, t38_918_b, t38orph_918orph_b, t38_orph_b,
s918_b, s918orph_b, t918_1935_b, t918orph_1935_b, t918_orph_b, f918_b, f918orph_b,
s1935_b, t1935_36_b, f1935_b, s36_b, f36_b];
```

boot_other_parameters

```
rng(767)

%%%%%%%%%%%%% t02_38

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "K2:K20";
opts.VariableNames = "t02_38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t02_38_data = tbl.t02_38transformed;
clear opts tbl

t02_38_boot = bootstrp(10000, @mean, t02_38_data);
t02_38_boot_mean = mean(t02_38_boot);
t02_38_boot_ci = bootci(10000, @mean, t02_38_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "T2:T14";
opts.VariableNames = "undt02_38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t02_38_less_data = tbl.undt02_38transformed;
clear opts tbl

t02_38_less_boot = bootstrp(10000, @mean, t02_38_less_data);
t02_38_less_boot_mean = mean(t02_38_less_boot);
t02_38_less_boot_ci = bootci(10000, @mean, t02_38_less_data);

%more poaching
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "AC2:AC7";
opts.VariableNames = "distt02_38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
```

```
t02_38_more_data = tbl.distt02_38transformed;
clear opts tbl

t02_38_more_boot = bootstrp(10000, @mean, t02_38_more_data);
t02_38_more_boot_mean = mean(t02_38_more_boot);
t02_38_more_boot_ci = bootci(10000, @mean, t02_38_more_data);

%%%%%%%%%%%%% t02_orph

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "M2:M20";
opts.VariableNames = "t02_orph02transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t02_orph_data = tbl.t02_orph02transformed;
clear opts tbl

t02_orph_boot = bootstrp(10000, @mean, t02_orph_data);
t02_orph_boot_mean = mean(t02_orph_boot);
t02_orph_boot_ci = bootci(10000, @mean, t02_orph_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "V2:V14";
opts.VariableNames = "undt02_orph02transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t02_orph_less_data = tbl.undt02_orph02transformed;
clear opts tbl

t02_orph_less_boot = bootstrp(10000, @mean, t02_orph_less_data);
t02_orph_less_boot_mean = mean(t02_orph_less_boot);
t02_orph_less_boot_ci = bootci(10000, @mean, t02_orph_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "AE2:AE7";
```

```
opts.VariableNames = "distt02_orph02transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t02_orph_more_data = tbl.distt02_orph02transformed;
clear opts tbl

t02_orph_more_boot = bootstrp(10000, @mean, t02_orph_more_data);
t02_orph_more_boot_mean = mean(t02_orph_more_boot);
t02_orph_more_boot_ci = bootci(10000, @mean, t02_orph_more_data);

%%%%%%%%%%%%%%% t38_918

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "K2:K20";
opts.VariableNames = "t38_918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38_918_data = tbl.t38_918transformed;
clear opts tbl

t38_918_boot = bootstrp(10000, @mean, t38_918_data);
t38_918_boot_mean = mean(t38_918_boot);
t38_918_boot_ci = bootci(10000, @mean, t38_918_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "U2:U14";
opts.VariableNames = "undt38_918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38_918_less_data = tbl.undt38_918transformed;
clear opts tbl

t38_918_less_boot = bootstrp(10000, @mean, t38_918_less_data);
t38_918_less_boot_mean = mean(t38_918_less_boot);
t38_918_less_boot_ci = bootci(10000, @mean, t38_918_less_data);

%more poaching
```

```
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "AE2:AE7";
opts.VariableNames = "distt38_918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38_918_more_data = tbl.distt38_918transformed;
clear opts tbl

t38_918_more_boot = bootstrp(10000, @mean, t38_918_more_data);
t38_918_more_boot_mean = mean(t38_918_more_boot);
t38_918_more_boot_ci = bootci(10000, @mean, t38_918_more_data);

%%%%%%%%%%%%%%%% t38orph_918orph

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 3-8";
opts.DataRange = "O3:O20";
opts.VariableNames = "torph38_orph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38orph_918orph_data = tbl.torph38_orph918transformed;
clear opts tbl

t38orph_918orph_boot = bootstrp(10000, @mean, t38orph_918orph_data);
t38orph_918orph_boot_mean = mean(t38orph_918orph_boot);
t38orph_918orph_boot_ci = bootci(10000, @mean, t38orph_918orph_data);

%less poaching

opts = spreadsheetImportOptions(""NumVariables"", 1);
opts.Sheet = "orphan 3-8";
opts.DataRange = "W3:W14";
opts.VariableNames = "undtorph38_orph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38orph_918orph_less_data = tbl.undtorph38_orph918transformed;
clear opts tbl

t38orph_918orph_less_boot = bootstrp(10000, @mean, t38orph_918orph_less_data);
```

```
t38orph_918orph_less_boot_mean = mean(t38orph_918orph_less_boot);
t38orph_918orph_less_boot_ci = bootci(10000, @mean, t38orph_918orph_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 3-8";
opts.DataRange = "AE2:AE7";
opts.VariableNames = "disttorph38_orph918transformed";
"opts.VariableTypes = ""double"";"
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38orph_918orph_more_data = tbl.disttorph38_orph918transformed;
clear opts tbl

t38orph_918orph_more_boot = bootstrp(10000, @mean, t38orph_918orph_more_data);
t38orph_918orph_more_boot_mean = mean(t38orph_918orph_more_boot);
t38orph_918orph_more_boot_ci = bootci(10000, @mean, t38orph_918orph_more_data);

%%%%%%%%%%%%%%%%%% t38_orph

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "M2:M20";
opts.VariableNames = "t38_orph38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38_orph_data = tbl.t38_orph38transformed;
clear opts tbl

t38_orph_boot = bootstrp(10000, @mean, t38_orph_data);
t38_orph_boot_mean = mean(t38_orph_boot);
t38_orph_boot_ci = bootci(10000, @mean, t38_orph_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "W2:W14";
opts.VariableNames = "undt38_orph38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
```

```
t38_orph_less_data = tbl.undt38_orph38transformed;
clear opts tbl

t38_orph_less_boot = bootstrp(10000, @mean, t38_orph_less_data);
t38_orph_less_boot_mean = mean(t38_orph_less_boot);
t38_orph_less_boot_ci = bootci(10000, @mean, t38_orph_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "AG2:AG7";
opts.VariableNames = "distt38_orph38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t38_orph_more_data = tbl.distt38_orph38transformed;
clear opts tbl

t38_orph_more_boot = bootstrp(10000, @mean, t38_orph_more_data);
t38_orph_more_boot_mean = mean(t38_orph_more_boot);
t38_orph_more_boot_ci = bootci(10000, @mean, t38_orph_more_data);

%%%%%%%%%%%%%%%%%% t918_1935

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "K2:K20";
opts.VariableNames = "t918_1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918_1935_data = tbl.t918_1935transformed;
clear opts tbl

t918_1935_boot = bootstrp(10000, @mean, t918_1935_data);
t918_1935_boot_mean = mean(t918_1935_boot);
t918_1935_boot_ci = bootci(10000, @mean, t918_1935_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "U2:U14";
```

```
opts.VariableNames = "undt918_1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918_1935_less_data = tbl.undt918_1935transformed;
clear opts tbl

t918_1935_less_boot = bootstrp(10000, @mean, t918_1935_less_data);
t918_1935_less_boot_mean = mean(t918_1935_less_boot);
t918_1935_less_boot_ci = bootci(10000, @mean, t918_1935_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "AE2:AE7";
opts.VariableNames = "distt918_1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918_1935_more_data = tbl.distt918_1935transformed;
clear opts tbl

t918_1935_more_boot = bootstrp(10000, @mean, t918_1935_more_data);
t918_1935_more_boot_mean = mean(t918_1935_more_boot);
t918_1935_more_boot_ci = bootci(10000, @mean, t918_1935_more_data);

%%%%%%%%%%%%%%%%%% t918orph_1935

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18";
opts.DataRange = "N4:N20";
opts.VariableNames = "torph918_1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918orph_1935_data = tbl.torph918_1935transformed;
clear opts tbl

t918orph_1935_boot = bootstrp(10000, @mean, t918orph_1935_data);
t918orph_1935_boot_mean = mean(t918orph_1935_boot);
t918orph_1935_boot_ci = bootci(10000, @mean, t918orph_1935_data);

%less poaching
```

```
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18";
opts.DataRange = "V4:V14";
opts.VariableNames = "undtorph918_1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918orph_1935_less_data = tbl.undtorph918_1935transformed;
clear opts tbl

t918orph_1935_less_boot = bootstrp(10000, @mean, t918orph_1935_less_data);
t918orph_1935_less_boot_mean = mean(t918orph_1935_less_boot);
t918orph_1935_less_boot_ci = bootci(10000, @mean, t918orph_1935_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18";
opts.DataRange = "AD2:AD7";
opts.VariableNames = "disttorph918_1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918orph_1935_more_data = tbl.disttorph918_1935transformed;
clear opts tbl

t918orph_1935_more_boot = bootstrp(10000, @mean, t918orph_1935_more_data);
t918orph_1935_more_boot_mean = mean(t918orph_1935_more_boot);
t918orph_1935_more_boot_ci = bootci(10000, @mean, t918orph_1935_more_data);

%%%%%%%%%%%%%%%%%% t918_orph

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "M2:M20";
opts.VariableNames = "t918_orph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918_orph_data = tbl.t918_orph918transformed;
clear opts tbl

t918_orph_boot = bootstrp(10000, @mean, t918_orph_data);
```

```
t918_orph_boot_mean = mean(t918_orph_boot);
t918_orph_boot_ci = bootci(10000, @mean, t918_orph_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "W2:W14";
opts.VariableNames = "undt918_orph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918_orph_less_data = tbl.undt918_orph918transformed;
clear opts tbl

t918_orph_less_boot = bootstrp(10000, @mean, t918_orph_less_data);
t918_orph_less_boot_mean = mean(t918_orph_less_boot);
t918_orph_less_boot_ci = bootci(10000, @mean, t918_orph_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "AG2:AG7";
opts.VariableNames = "distt918_orph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t918_orph_more_data = tbl.distt918_orph918transformed;
clear opts tbl


t918_orph_more_boot = bootstrp(10000, @mean, t918_orph_more_data);
t918_orph_more_boot_mean = mean(t918_orph_more_boot);
t918_orph_more_boot_ci = bootci(10000, @mean, t918_orph_more_data);

%%%%%%%%%%%%%%% f918

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18 f";
opts.DataRange = "L2:L20";
opts.VariableNames = "f918transformed";
opts.VariableTypes = "double";
```

```
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f918_data = tbl.f918transformed;
clear opts tbl

f918_boot = bootstrp(10000, @mean, f918_data);
f918_boot_mean = mean(f918_boot);
f918_boot_ci = bootci(10000, @mean, f918_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18 f";
opts.DataRange = "R2:R14";
opts.VariableNames = "undf918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f918_less_data = tbl.undf918transformed;
clear opts tbl

f918_less_boot = bootstrp(10000, @mean, f918_less_data);
f918_less_boot_mean = mean(f918_less_boot);
f918_less_boot_ci = bootci(10000, @mean, f918_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18 f";
opts.DataRange = "X2:X7";
opts.VariableNames = "distf918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f918_more_data= tbl.distf918transformed;
clear opts tbl

f918_more_boot = bootstrp(10000, @mean, f918_more_data);
f918_more_boot_mean = mean(f918_more_boot);
f918_more_boot_ci = bootci(10000, @mean, f918_more_data);

%%%%%%%%%%%%%%% f918orph

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
```

```
opts.Sheet = "orphan 9-18 f";
opts.DataRange = "L4:L20";
opts.VariableNames = "forph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f918orph_data = tbl.forph918transformed;
clear opts tbl

f918orph_boot = bootstrp(10000, @mean, f918orph_data);
f918orph_boot_mean = mean(f918orph_boot);
f918orph_boot_ci = bootci(10000, @mean, f918orph_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18 f";
opts.DataRange = "R4:R14";
opts.VariableNames = "undforph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f918orph_less_data = tbl.undforph918transformed;
clear opts tbl

f918orph_less_boot = bootstrp(10000, @mean, f918orph_less_data);
f918orph_less_boot_mean = mean(f918orph_less_boot);
f918orph_less_boot_ci = bootci(10000, @mean, f918orph_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18 f";
opts.DataRange = "X2:X7";
opts.VariableNames = "distforph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f918orph_more_data = tbl.distforph918transformed;
clear opts tbl

f918orph_more_boot = bootstrp(10000, @mean, f918orph_more_data);
f918orph_more_boot_mean = mean(f918orph_more_boot);
f918orph_more_boot_ci = bootci(10000, @mean, f918orph_more_data);

%%%%%%%%%%%%%%%%%%%%%%% s1935
```

```
%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35";
opts.DataRange = "H2:H20";
opts.VariableNames = "s1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s1935_data = tbl.s1935transformed;
clear opts tbl

s1935_boot = bootstrp(10000, @mean, s1935_data);
s1935_boot_mean = mean(s1935_boot);
s1935_boot_ci = bootci(10000, @mean, s1935_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35";
opts.DataRange = "P2:P14";
opts.VariableNames = "unds1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s1935_less_data = tbl.unds1935transformed;
clear opts tbl

s1935_less_boot = bootstrp(10000, @mean, s1935_less_data);
s1935_less_boot_mean = mean(s1935_less_boot);
s1935_less_boot_ci = bootci(10000, @mean, s1935_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35";
opts.DataRange = "X2:X7";
opts.VariableNames = "dists1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s1935_more_data = tbl.dists1935transformed;
clear opts tbl

s1935_more_boot = bootstrp(10000, @mean, s1935_more_data);
```

```
s1935_more_boot_mean = mean(s1935_more_boot);
s1935_more_boot_ci = bootci(10000, @mean, s1935_more_data);

%%%%%%%%%%%%%%%%%%% t1935_36

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35";
opts.DataRange = "I2:I20";
opts.VariableNames = "t1935_35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t1935_36_data = tbl.t1935_35transformed;
clear opts tbl

t1935_36_boot = bootstrp(10000, @mean, t1935_36_data);
t1935_36_boot_mean = mean(t1935_36_boot);
t1935_36_boot_ci = bootci(10000, @mean, t1935_36_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35";
opts.DataRange = "Q2:Q14";
opts.VariableNames = "undt1935_35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
t1935_36_less_data = tbl.undt1935_35transformed;
clear opts tbl

t1935_36_less_boot = bootstrp(10000, @mean, t1935_36_less_data);
t1935_36_less_boot_mean = mean(t1935_36_less_boot);
t1935_36_less_boot_ci = bootci(10000, @mean, t1935_36_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35";
opts.DataRange = "Y2:Y7";
opts.VariableNames = "distt1935_35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
```

```
t1935_36_more_data = tbl.distt1935_35transformed;
clear opts tbl

t1935_36_more_boot = bootstrp(10000, @mean, t1935_36_more_data);
t1935_36_more_boot_mean = mean(t1935_36_more_boot);
t1935_36_more_boot_ci = bootci(10000, @mean, t1935_36_more_data);

%%%%%%%%%%%%%%%%% f1935

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35 f";
opts.DataRange = "L2:L20";
opts.VariableNames = "f1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f1935_data = tbl.f1935transformed;
clear opts tbl

f1935_boot = bootstrp(10000, @mean, f1935_data);
f1935_boot_mean = mean(f1935_boot);
f1935_boot_ci = bootci(10000, @mean, f1935_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35 f";
opts.DataRange = "R2:R14";
opts.VariableNames = "undf1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f1935_less_data = tbl.undf1935transformed;
clear opts tbl

f1935_less_boot = bootstrp(10000, @mean, f1935_less_data);
f1935_less_boot_mean = mean(f1935_less_boot);
f1935_less_boot_ci = bootci(10000, @mean, f1935_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "19-35 f";
opts.DataRange = "X2:X7";
```

```
opts.VariableNames = "distf1935transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f1935_more_data = tbl.distf1935transformed;
clear opts tbl

f1935_more_boot = bootstrp(10000, @mean, f1935_more_data);
f1935_more_boot_mean = mean(f1935_more_boot);
f1935_more_boot_ci = bootci(10000, @mean, f1935_more_data);

%%%%%%%%%%%%%%%%%%% s36

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = ">35";
opts.DataRange = "F2:F20";
opts.VariableNames = "s35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s36_data = tbl.s35transformed;
clear opts tbl

s36_boot = bootstrp(10000, @mean, s36_data);
s36_boot_mean = mean(s36_boot);
s36_boot_ci = bootci(10000, @mean, s36_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = ">35";
opts.DataRange = "L2:L14";
opts.VariableNames = "unds35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s36_less_data = tbl.unds35transformed;
clear opts tbl

s36_less_boot = bootstrp(10000, @mean, s36_less_data);
s36_less_boot_mean = mean(s36_less_boot);
s36_less_boot_ci = bootci(10000, @mean, s36_less_data);

%more poaching
```

```
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = ">35";
opts.DataRange = "R2:R7";
opts.VariableNames = "dists35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s36_more_data = tbl.dists35transformed;
clear opts tbl

s36_more_boot = bootstrp(10000, @mean, s36_more_data);
s36_more_boot_mean = mean(s36_more_boot);
s36_more_boot_ci = bootci(10000, @mean, s36_more_data);

%%%%%%%%%%%%%%%%%% f36

%all data

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = ">35 f";
opts.DataRange = "L2:L20";
opts.VariableNames = "f35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f36_data = tbl.f35transformed;
clear opts tbl

f36_boot = bootstrp(10000, @mean, f36_data);
f36_boot_mean = mean(f36_boot);
f36_boot_ci = bootci(10000, @mean, f36_data);

%less poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = ">35 f";
opts.DataRange = "R2:R14";
opts.VariableNames = "undf35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f36_less_data = tbl.undf35transformed;
clear opts tbl

f36_less_boot = bootstrp(10000, @mean, f36_less_data);
```

```
f36_less_boot_mean = mean(f36_less_boot);
f36_less_boot_ci = bootci(10000, @mean, f36_less_data);

%more poaching

opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = ">35 f";
opts.DataRange = "X2:X7";
opts.VariableNames = "distf35transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
f36_more_data = tbl.distf35transformed;
clear opts tbl

f36_more_boot = bootstrp(10000, @mean, f36_more_data);
f36_more_boot_mean = mean(f36_more_boot);
f36_more_boot_ci = bootci(10000, @mean, f36_more_data);
```

bootstrap

```
rng(767)

%%%%%%%%%%%%%%%% Import data

%s02_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "L2:L20";
opts.VariableNames = "s02transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s02_data = tbl.s02transformed;
clear opts tbl

%s02_less_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "U2:U14";
opts.VariableNames = "unds02transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s02_less_data = tbl.unds02transformed;
clear opts tbl

%s02_more_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "0-2";
opts.DataRange = "AD2:AD7";
opts.VariableNames = "dists02transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s02_more_data = tbl.dists02transformed;
clear opts tbl

%s38_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "L2:L20";
opts.VariableNames = "s38transformed";
opts.VariableTypes = "double";
```

```
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s38_data = tbl.s38transformed;
clear opts tbl

%s38_less_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "V2:V14";
opts.VariableNames = "unds38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s38_less_data = tbl.unds38transformed;
clear opts tbl

%s38_more_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "3-8";
opts.DataRange = "AF2:AF7";
opts.VariableNames = "dists38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s38_more_data = tbl.dists38transformed;
clear opts tbl

%sorph38_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 3-8";
opts.DataRange = "P3:P20";
opts.VariableNames = "sorph38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
sorph38_data = tbl.sorph38transformed;
clear opts tbl

%sorph38_less_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 3-8";
opts.DataRange = "X3:X14";
opts.VariableNames = "undsorph38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
```

```
sorph38_less_data = tbl.undsorph38transformed;
clear opts tbl

%sorph38_more_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 3-8";
opts.DataRange = "AF2:AF7";
opts.VariableNames = "distsorph38transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
sorph38_more_data = tbl.distsorph38transformed;
clear opts tbl

%s918_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "L2:L20";
opts.VariableNames = "s918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s918_data = tbl.s918transformed;
clear opts tbl

%s918_less_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "V2:V14";
opts.VariableNames = "unds918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s918_less_data = tbl.unds918transformed;
clear opts tbl

%s918_more_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "9-18";
opts.DataRange = "AF2:AF7";
opts.VariableNames = "dists918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
s918_more_data = tbl.dists918transformed;
clear opts tbl
```

```
%sorph918_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18";
opts.DataRange = "O4:O20";
opts.VariableNames = "sorph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
sorph918_data = tbl.sorph918transformed;
clear opts tbl

%sorph918_less_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18";
opts.DataRange = "W4:W14";
opts.VariableNames = "undsorph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
sorph918_less_data = tbl.undsorph918transformed;
clear opts tbl

%sorph918_more_data
opts = spreadsheetImportOptions("NumVariables", 1);
opts.Sheet = "orphan 9-18";
opts.DataRange = "AE2:AE7";
opts.VariableNames = "distsorph918transformed";
opts.VariableTypes = "double";
tbl = readtable("/Users/jennaparker/Dropbox/Demography/Appendices/PAppendix 1.xls", opts,
"UseExcel", false);
sorph918_more_data = tbl.distsorph918transformed;
clear opts tbl

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% Bootstrap all data

%survival 0-2 nonorphan vs. orphan

s02_boot = bootstrp(10000, @mean, s02_data);
s02_boot_mean = mean(s02_boot);
s02_boot_ci = bootci(10000, @mean, s02_data);

s02orph_boot = zeros(10000,1);

%survival 3-8 nonorphan vs. orphan
```

```
s38_boot = bootstrp(10000, @mean, s38_data);
s38_boot_mean = mean(s38_boot);
s38_boot_ci = bootci(10000, @mean, s38_data);

s38orph_boot = bootstrp(10000, @mean, sorph38_data);
s38orph_boot_mean = mean(s38orph_boot);
s38orph_boot_ci = bootci(10000, @mean, sorph38_data);

%survival 9-18 nonorphan vs. orphan

s918_boot = bootstrp(10000, @mean, s918_data);
s918_boot_mean = mean(s918_boot);
s918_boot_ci = bootci(10000, @mean, s918_data);

s918orph_boot = bootstrp(10000, @mean, sorph918_data);
s918orph_boot_mean = mean(s918orph_boot);
s918orph_boot_ci = bootci(10000, @mean, sorph918_data);

%%%%%%%%%%%%%%%%%%%%%% less poaching

%survival 0-2 nonorphan vs. orphan

s02_less_boot = bootstrp(10000, @mean, s02_less_data);
s02_less_boot_mean = mean(s02_less_boot);
s02_less_boot_ci = bootci(10000, @mean, s02_less_data);

s02orph_less_boot = zeros(10000,1);

%survival 3-8 nonorphan vs. orphan

s38_less_boot = bootstrp(10000, @mean, s38_less_data);
s38_less_boot_mean = mean(s38_less_boot);
s38_less_boot_ci = bootci(10000, @mean, s38_less_data);

s38orph_less_boot = bootstrp(10000, @mean, sorph38_less_data);
s38orph_less_boot_mean = mean(s38orph_less_boot);
s38orph_less_boot_ci = bootci(10000, @mean, sorph38_less_data);

%survival 9-18 nonorphan vs. orphan

s918_less_boot = bootstrp(10000, @mean, s918_less_data);
s918_less_boot_mean = mean(s918_less_boot);
s918_less_boot_ci = bootci(10000, @mean, s918_less_data);

s918orph_less_boot = bootstrp(10000, @mean, sorph918_less_data);
s918orph_less_boot_mean = mean(s918orph_less_boot);
```

```
s918orph_less_boot_ci = bootci(10000, @mean, sorph918_less_data);

%%%%%%%%%%%%%%%%%%%%% more poaching

%survival 0-2 nonorphan vs. orphan

s02_more_boot = bootstrp(10000, @mean, s02_more_data);
s02_more_boot_mean = mean(s02_more_boot);
s02_more_boot_ci = bootci(10000, @mean, s02_more_data);

s02orph_more_boot = zeros(10000,1);

%survival 3-8 nonorphan vs. orphan

s38_more_boot = bootstrp(10000, @mean, s38_more_data);
s38_more_boot_mean = mean(s38_more_boot);
s38_more_boot_ci = bootci(10000, @mean, s38_more_data);

s38orph_more_boot = bootstrp(10000, @mean,sorph38_more_data);
s38orph_more_boot_mean = mean(s38orph_more_boot);
s38orph_more_boot_ci = bootci(10000, @mean, sorph38_more_data);

%survival 9-18 nonorphan vs. orphan

s918_more_boot = bootstrp(10000, @mean, s918_more_data);
s918_more_boot_mean = mean(s918_more_boot);
s918_more_boot_ci = bootci(10000, @mean, s918_more_data);

s918orph_more_boot = bootstrp(10000, @mean, sorph918_more_data);
s918orph_more_boot_mean = mean(s918orph_more_boot);
s918orph_more_boot_ci = bootci(10000, @mean, sorph918_more_data);
```

eigenvalues

```
beta_parameters;
%beta_parameters_less_poaching;
%beta_parameters_more_poaching;
%beta_parameters_irr;
LHS_draws;
LHS_matrices;

EIGENVALUES = zeros(nsample,1);

for k = 1:nsample
   EIGENVALUES(k,1) = max(abs(eig(LHS_MATRICES(:,:,k))));
end

lambda_median = median(EIGENVALUES(:,1));
lambda_mean = mean(EIGENVALUES(:,1));
```

K_S_tests

```
bootstrap_direct_data;

%%%%%%%%%%%%%%% all data

%3 to 8-year-old comparisons

s38 = s38_data;
s38orph = sorph38_data;

[h,p,ks2stat] = kstest2(s38, s38orph)

%9 to 13-year-old comparisons

s918 = s918_data;
s918orph = sorph918_data;

[h,p,ks2stat] = kstest2(s918, s918orph)

%%%%%%%%%%%%%% less poaching

%3 to 8-year-old comparisons

s38 = s38_less_data;
s38orph = sorph38_less_data;

[h,p,ks2stat] = kstest2(s38, s38orph)

%9 to 18-year-old comparison

s918 = s918_less_data;
s918orph = sorph918_less_data;

[h,p,ks2stat] = kstest2(s918, s918orph)

%%%%%%%%%%%%%%% more poaching

%3 to 8-year-old comparisons

s38 = s38_more_data;
s38orph = sorph38_more_data;

[h,p,ks2stat] = kstest2(s38, s38orph)

%9 to 18-year-old comparison
```

```
s918 = s918_more_data;
s918orph = sorph918_more_data;

[h,p,ks2stat] = kstest2(s918, s918orph)
```

lambdas

```
bootstrap_direct_data;
boot_other_parameters;

%remove data from years without all orphan parameters

s02_data(1:2) = [];
s02_less_data(1:2) = [];
t02_38_data(1:2) = [];
t02_38_less_data(1:2) = [];
t02_orph_data(1:2) = [];
t02_orph_less_data(1:2) = [];
s38_data(1:2) = [];
s38_less_data(1:2) = [];
sorph38_data(1) = [];
sorph38_less_data(1) = [];
t38_918_data(1:2) = [];
t38_918_less_data(1:2) = [];
t38orph_918orph_data(1) = [];
t38orph_918orph_less_data(1) = [];
t38_orph_data(1:2) = [];
t38_orph_less_data(1:2) = [];
s918_data(1:2) = [];
s918_less_data(1:2) = [];
t918_1935_data(1:2) = [];
t918_1935_less_data(1:2) = [];
t918_orph_data(1:2) = [];
t918_orph_less_data(1:2) = [];
f918_data(1:2) = [];
f918_less_data(1:2) = [];
s1935_data(1:2) = [];
s1935_less_data(1:2) = [];
t1935_36_data(1:2) = [];
t1935_36_less_data(1:2) = [];
f1935_data(1:2) = [];
f1935_less_data(1:2) = [];
s36_data(1:2) = [];
s36_less_data(1:2) = [];
f36_data(1:2) = [];
f36_less_data(1:2) = [];

%all data

ACTUAL = [s02_data, t02_38_data, t02_orph_data, s38_data, sorph38_data, t38_918_data,
t38orph_918orph_data, t38_orph_data, s918_data, sorph918_data, t918_1935_data,
```

```
t918orph_1935_data, t918_orph_data, f918_data, f918orph_data, s1935_data, t1935_36_data,
f1935_data, s36_data, f36_data];
nstages = 8;
nsample = 17;
MATRICES = zeros(nstages,nstages,nsample);


for k = 1:nsample
   MATRICES(1,1,:) = ACTUAL(:,1).*(1-ACTUAL(:,2)-ACTUAL(:,3));
   MATRICES(1:8,2,:) = 0;
   MATRICES(1,3:4,:) = 0;
   MATRICES(1,5,:) = ACTUAL(:,14).*ACTUAL(:,9).*(1-ACTUAL(:,11)-ACTUAL(:,13));
   MATRICES(1,6,:) = ACTUAL(:,15).*ACTUAL(:,10).*(1-ACTUAL(:,12));
   MATRICES(1,7,:) = ACTUAL(:,16).*ACTUAL(:,18).*(1-ACTUAL(:,17));
   MATRICES(1,8,:) = ACTUAL(:,20).*ACTUAL(:,19);
   MATRICES(2,1,:) = ACTUAL(:,3).*0;
   MATRICES(2,3:8,:) = 0;
   MATRICES(3,1,:) = ACTUAL(:,2).*ACTUAL(:,1);
   MATRICES(3,3,:) = ACTUAL(:,4).*(1-ACTUAL(:,6)-ACTUAL(:,8));
   MATRICES(3,4:8,:) = 0;
   MATRICES(4:8,1,:) = 0;
   MATRICES(4,3,:) = ACTUAL(:,8).*ACTUAL(:,5);
   MATRICES(4,4,:) = ACTUAL(:,5).*(1-ACTUAL(:,7));
   MATRICES(4,5:8,:) = 0;
   MATRICES(5,3,:) = ACTUAL(:,6).*ACTUAL(:,4);
   MATRICES(5,4,:) = 0;
   MATRICES(5,5,:) = ACTUAL(:,9).*(1-ACTUAL(:,11)-ACTUAL(:,13));
   MATRICES(5,6:8,:) = 0;
   MATRICES(6:8,3,:) = 0;
   MATRICES(6,4,:) = ACTUAL(:,7).*ACTUAL(:,5);
   MATRICES(6,5,:) = ACTUAL(:,13).*ACTUAL(:,10);
   MATRICES(6,6,:) = ACTUAL(:,10).*(1-ACTUAL(:,12));
   MATRICES(6,7:8,:) = 0;
   MATRICES(7:8,4,:) = 0;
   MATRICES(7,5,:) = ACTUAL(:,9).*ACTUAL(:,11);
   MATRICES(7,6,:) = ACTUAL(:,10).*ACTUAL(:,12);
   MATRICES(7,7,:) = ACTUAL(:,16).*(1-ACTUAL(:,17));
   MATRICES(7,8,:) = 0;
   MATRICES(8,5:6,:) = 0;
   MATRICES(8,7,:) = ACTUAL(:,17).*ACTUAL(:,16);
   MATRICES(8,8,:) = ACTUAL(:,19);
end

EIGENVALUES = zeros(nsample,1);

for k = 1:nsample
```

```
   EIGENVALUES(k,1) = max(abs(eig(MATRICES(:,:,k))));
end

lambda_boot = bootstrp(10000, @mean, EIGENVALUES);
lambda_boot_mean = mean(lambda_boot);
lambda_boot_ci = bootci(10000, @mean, EIGENVALUES);

%less poaching

ACTUAL_less = [s02_less_data, t02_38_less_data, t02_orph_less_data, s38_less_data,
sorph38_less_data, t38_918_less_data, t38orph_918orph_less_data, t38_orph_less_data,
s918_less_data, sorph918_less_data, t918_1935_less_data, t918orph_1935_less_data,
t918_orph_less_data, f918_less_data, f918orph_less_data, s1935_less_data, t1935_36_less_data,
f1935_less_data, s36_less_data, f36_less_data];
nstages = 8;
nsample = 11;
MATRICES_less = zeros(nstages,nstages,nsample);


for k = 1:nsample
   MATRICES_less(1,1,:) = ACTUAL_less(:,1).*(1-ACTUAL_less(:,2)-ACTUAL_less(:,3));
   MATRICES_less(1:8,2,:) = 0;
   MATRICES_less(1,3:4,:) = 0;
   MATRICES_less(1,5,:) = ACTUAL_less(:,14).*ACTUAL_less(:,9).*(1-ACTUAL_less(:,11)-
ACTUAL_less(:,13));
   MATRICES_less(1,6,:) = ACTUAL_less(:,15).*ACTUAL_less(:,10).*(1-
ACTUAL_less(:,12));
   MATRICES_less(1,7,:) = ACTUAL_less(:,16).*ACTUAL_less(:,18).*(1-
ACTUAL_less(:,17));
   MATRICES_less(1,8,:) = ACTUAL_less(:,20).*ACTUAL_less(:,19);
   MATRICES_less(2,1,:) = ACTUAL_less(:,3).*0;
   MATRICES_less(2,3:8,:) = 0;
   MATRICES_less(3,1,:) = ACTUAL_less(:,2).*ACTUAL_less(:,1);
   MATRICES_less(3,3,:) = ACTUAL_less(:,4).*(1-ACTUAL_less(:,6)-ACTUAL_less(:,8));
   MATRICES_less(3,4:8,:) = 0;
   MATRICES_less(4:8,1,:) = 0;
   MATRICES_less(4,3,:) = ACTUAL_less(:,8).*ACTUAL_less(:,5);
   MATRICES_less(4,4,:) = ACTUAL_less(:,5).*(1-ACTUAL_less(:,7));
   MATRICES_less(4,5:8,:) = 0;
   MATRICES_less(5,3,:) = ACTUAL_less(:,6).*ACTUAL_less(:,4);
   MATRICES_less(5,4,:) = 0;
   MATRICES_less(5,5,:) = ACTUAL_less(:,9).*(1-ACTUAL_less(:,11)-ACTUAL_less(:,13));
   MATRICES_less(5,6:8,:) = 0;
   MATRICES_less(6:8,3,:) = 0;
   MATRICES_less(6,4,:) = ACTUAL_less(:,7).*ACTUAL_less(:,5);
   MATRICES_less(6,5,:) = ACTUAL_less(:,13).*ACTUAL_less(:,10);
```

```
    MATRICES_less(6,6,:) = ACTUAL_less(:,10).*(1-ACTUAL_less(:,12));
    MATRICES_less(6,7:8,:) = 0;
    MATRICES_less(7:8,4,:) = 0;
    MATRICES_less(7,5,:) = ACTUAL_less(:,9).*ACTUAL_less(:,11);
    MATRICES_less(7,6,:) = ACTUAL_less(:,10).*ACTUAL_less(:,12);
    MATRICES_less(7,7,:) = ACTUAL_less(:,16).*(1-ACTUAL_less(:,17));
    MATRICES_less(7,8,:) = 0;
    MATRICES_less(8,5:6,:) = 0;
    MATRICES_less(8,7,:) = ACTUAL_less(:,17).*ACTUAL_less(:,16);
    MATRICES_less(8,8,:) = ACTUAL_less(:,19);
end

EIGENVALUES_less = zeros(nsample,1);

for k = 1:nsample
    EIGENVALUES_less(k,1) = max(abs(eig(MATRICES_less(:,:,k))));
end

lambda_less_boot = bootstrp(10000, @mean, EIGENVALUES_less);
lambda_less_boot_mean = mean(lambda_less_boot);
lambda_less_boot_ci = bootci(10000, @mean, EIGENVALUES_less);

%more poaching

ACTUAL_more = [s02_more_data, t02_38_more_data, t02_orph_more_data, s38_more_data,
sorph38_more_data, t38_918_more_data, t38orph_918orph_more_data, t38_orph_more_data,
s918_more_data, sorph918_more_data, t918_1935_more_data, t918orph_1935_more_data,
t918_orph_more_data, f918_more_data, f918orph_more_data, s1935_more_data,
t1935_36_more_data, f1935_more_data, s36_more_data, f36_more_data];
nstages = 8;
nsample = 6;
MATRICES_more = zeros(nstages,nstages,nsample);


for k = 1:nsample
    MATRICES_more(1,1,:) = ACTUAL_more(:,1).*(1-ACTUAL_more(:,2)-
ACTUAL_more(:,3));
    MATRICES_more(1:8,2,:) = 0;
    MATRICES_more(1,3:4,:) = 0;
    MATRICES_more(1,5,:) = ACTUAL_more(:,14).*ACTUAL_more(:,9).*(1-
ACTUAL_more(:,11)-ACTUAL_more(:,13));
    MATRICES_more(1,6,:) = ACTUAL_more(:,15).*ACTUAL_more(:,10).*(1-
ACTUAL_more(:,12));
    MATRICES_more(1,7,:) = ACTUAL_more(:,16).*ACTUAL_more(:,18).*(1-
ACTUAL_more(:,17));
    MATRICES_more(1,8,:) = ACTUAL_more(:,20).*ACTUAL_more(:,19);
```

```
    MATRICES_more(2,1,:) = ACTUAL_more(:,3).*0;
    MATRICES_more(2,3:8,:) = 0;
    MATRICES_more(3,1,:) = ACTUAL_more(:,2).*ACTUAL_more(:,1);
    MATRICES_more(3,3,:) = ACTUAL_more(:,4).*(1-ACTUAL_more(:,6)-
ACTUAL_more(:,8));
    MATRICES_more(3,4:8,:) = 0;
    MATRICES_more(4:8,1,:) = 0;
    MATRICES_more(4,3,:) = ACTUAL_more(:,8).*ACTUAL_more(:,5);
    MATRICES_more(4,4,:) = ACTUAL_more(:,5).*(1-ACTUAL_more(:,7));
    MATRICES_more(4,5:8,:) = 0;
    MATRICES_more(5,3,:) = ACTUAL_more(:,6).*ACTUAL_more(:,4);
    MATRICES_more(5,4,:) = 0;
    MATRICES_more(5,5,:) = ACTUAL_more(:,9).*(1-ACTUAL_more(:,11)-
ACTUAL_more(:,13));
    MATRICES_more(5,6:8,:) = 0;
    MATRICES_more(6:8,3,:) = 0;
    MATRICES_more(6,4,:) = ACTUAL_more(:,7).*ACTUAL_more(:,5);
    MATRICES_more(6,5,:) = ACTUAL_more(:,13).*ACTUAL_more(:,10);
    MATRICES_more(6,6,:) = ACTUAL_more(:,10).*(1-ACTUAL_more(:,12));
    MATRICES_more(6,7:8,:) = 0;
    MATRICES_more(7:8,4,:) = 0;
    MATRICES_more(7,5,:) = ACTUAL_more(:,9).*ACTUAL_more(:,11);
    MATRICES_more(7,6,:) = ACTUAL_more(:,10).*ACTUAL_more(:,12);
    MATRICES_more(7,7,:) = ACTUAL_more(:,16).*(1-ACTUAL_more(:,17));
    MATRICES_more(7,8,:) = 0;
    MATRICES_more(8,5:6,:) = 0;
    MATRICES_more(8,7,:) = ACTUAL_more(:,17).*ACTUAL_more(:,16);
    MATRICES_more(8,8,:) = ACTUAL_more(:,19);
end

EIGENVALUES_more = zeros(nsample,1);

for k = 1:nsample
    EIGENVALUES_more(k,1) = max(abs(eig(MATRICES_more(:,:,k))));
end

lambda_more_boot = bootstrp(10000, @mean, EIGENVALUES_more);
lambda_more_boot_mean = mean(lambda_more_boot);
lambda_more_boot_ci = bootci(10000, @mean, EIGENVALUES_more);
```

LHS_draws

```
beta_parameters;
%beta_parameters_less_poaching;
%beta_parameters_more_poaching;
%beta_parameters_irr;

nsample = 10000;
nvar = 20;
%nvar = 22; %irreducible
X = lhsdesign(nsample, nvar);
LHS_DRAWS = zeros(nsample, nvar);

for j=1:nvar
   LHS_DRAWS(:,j) = betainv(X(:,j), AB(1,j), AB(2,j));
end

%change t02_orph column so that it correlates with adult survival

t02_orph_sorted = sort(LHS_DRAWS(:,3)); %sort t02_orph values

t02_orph_sorted_ncolumns = 8;  %break t02_orph_sorted into a matrix of 8 (ordered) columns
t02_orph_sorted_nrows = nsample/t02_orph_sorted_ncolumns;
t02_orph_sorted_matrix = zeros(t02_orph_sorted_nrows,t02_orph_sorted_ncolumns);
for j=1:t02_orph_sorted_ncolumns
   if j==1
      t02_orph_sorted_matrix(1:t02_orph_sorted_nrows,j) =
t02_orph_sorted(j:j*t02_orph_sorted_nrows);
   else
   t02_orph_sorted_matrix(1:t02_orph_sorted_nrows,j) =
t02_orph_sorted(t02_orph_sorted_nrows*(j-1)+1:j*t02_orph_sorted_nrows);
   end
end

s918orph_sorted = sort(LHS_DRAWS(:,10)); %sort survival of 9-18 orphan class;

s918orph_sorted_ncolumns = 2;  %break spost918_orph_sorted into a matrix of 2 (ordered)
columns
s918orph_sorted_nrows = nsample/s918orph_sorted_ncolumns;
s918orph_sorted_matrix = zeros(s918orph_sorted_nrows,s918orph_sorted_ncolumns);
for j=1:s918orph_sorted_ncolumns
   if j==1
      s918orph_sorted_matrix(1:s918orph_sorted_nrows,j) =
s918orph_sorted(j:j*s918orph_sorted_nrows);
   else
```

```
   s918orph_sorted_matrix(1:s918orph_sorted_nrows,j) =
s918orph_sorted(s918orph_sorted_nrows*(j-1)+1:j*s918orph_sorted_nrows);
   end
end

s918_sorted = sort(LHS_DRAWS(:,9)); %sort survival of 9-18 nonorphan class;

uneven_divisor = 3; %nsample not divisible by 3
cutoff_1 = round(nsample/uneven_divisor);
cutoff_2 = round((nsample/uneven_divisor)*2);

s1935_sorted = sort(LHS_DRAWS(:,16)); %sort survival of 1935; divisor used will also be
uneven_divisor

s36_sorted = sort(LHS_DRAWS(:,19)); %sort survival of >35; divisor used will also be
uneven_divisor

%arrange t02_orph values according to adult survival values

for i=1:nsample
   if LHS_DRAWS(i,10) <= s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1)
& LHS_DRAWS(i,9) <= s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %1
      LHS_DRAWS(i,3) =
datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns)),1,'Replace',false); %1

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %2
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
1)),1,'Replace',false); %2

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %3
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %3

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %4
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
1)),1,'Replace',false); %4
```

```
   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %5
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %5

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %6
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %6

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %7
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
1)),1,'Replace',false); %7

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %8
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %8

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %9
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %9

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %10
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %10

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
```

```
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %11
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %11

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %12
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %12

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %13
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %13

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %14
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %14

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %15
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %15

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %16
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %16

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) <= s36_sorted(cutoff_1); %17
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      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %17

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_1); %18
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %18

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %19
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
1)),1,'Replace',false); %19

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_2); %20
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %20

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %21
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %21

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %22
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %22

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
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<= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_2); %23
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %23

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %24
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %24

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_2); %25
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %25

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %26
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %26

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_2); %27
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %27

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_2); %28
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %28
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   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %29
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %29

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) &
LHS_DRAWS(i,19) <= s36_sorted(cutoff_2); %30
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %30

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %31
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %31

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_2); %32
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %32

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %33
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %33

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %34
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      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %34

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19)
<= s36_sorted(cutoff_2); %35
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %35

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_1) & LHS_DRAWS(i,19) <=
s36_sorted(cutoff_2); %36
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
6)),1,'Replace',false); %36

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %37
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
2)),1,'Replace',false); %37

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %38
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %38

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %39
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %39

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %40
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %40
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   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_1) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %41
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %41

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_1) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %42
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %42

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %43
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
3)),1,'Replace',false); %43

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %44
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %44

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %45
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %45

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %46
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %46

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
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s918_sorted(cutoff_1) & LHS_DRAWS(i,9) > s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_1) & LHS_DRAWS(i,16) <= s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %47
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %47

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_1) & LHS_DRAWS(i,16)
<= s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %48
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
6)),1,'Replace',false); %48

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %49
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
4)),1,'Replace',false); %49

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %50
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %50

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %51
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
6)),1,'Replace',false); %51

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %52
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
5)),1,'Replace',false); %52

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted(cutoff_2) & LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %53
```

```
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
6)),1,'Replace',false); %53

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) > s1935_sorted(cutoff_2) &
LHS_DRAWS(i,19) > s36_sorted(cutoff_2); %54
      LHS_DRAWS(i,3) = datasample(t02_orph_sorted_matrix(:,(t02_orph_sorted_ncolumns-
7)),1,'Replace',false); %54

   end
end

%change t38_orph column so that it correlates with adult survival

t38_orph_sorted = sort(LHS_DRAWS(:,8)); %sort t38_orph values
uneven_divisor_2 = 12; %nsample not divisible by 11
cutoff_2_1 = round(nsample/uneven_divisor_2);
cutoff_2_2 = round((nsample/uneven_divisor_2)*2);
cutoff_2_3 = round((nsample/uneven_divisor_2)*3);
cutoff_2_4 = round((nsample/uneven_divisor_2)*4);
cutoff_2_5 = round((nsample/uneven_divisor_2)*5);
cutoff_2_6 = round((nsample/uneven_divisor_2)*6);
cutoff_2_7 = round((nsample/uneven_divisor_2)*7);
cutoff_2_8 = round((nsample/uneven_divisor_2)*8);
cutoff_2_9 = round((nsample/uneven_divisor_2)*9);
cutoff_2_10 = round((nsample/uneven_divisor_2)*10);
cutoff_2_11 = round((nsample/uneven_divisor_2)*11);

%for s918orph, use s918orph_sorted_matrix
%for s918, use original cutoffs (cutoff_1 and cutoff_2)

%make a 5 X 2000 ordered matrix for s1935

s1935_sorted_ncolumns = 5;
s1935_sorted_nrows = nsample/s1935_sorted_ncolumns;
s1935_sorted_matrix = zeros(s1935_sorted_nrows,s1935_sorted_ncolumns);
for j=1:s1935_sorted_ncolumns
   if j==1
      s1935_sorted_matrix(1:s1935_sorted_nrows,j) = s1935_sorted(j:j*s1935_sorted_nrows);
   else
   s1935_sorted_matrix(1:s1935_sorted_nrows,j) = s1935_sorted(s1935_sorted_nrows*(j-
1)+1:j*s1935_sorted_nrows);
   end
end
```

```
%make a 5 X 2000 ordered matrix for s36

s36_sorted_ncolumns = 5;
s36_sorted_nrows = nsample/s36_sorted_ncolumns;
s36_sorted_matrix = zeros(s36_sorted_nrows,s36_sorted_ncolumns);
for j=1:s36_sorted_ncolumns
   if j==1
      s36_sorted_matrix(1:s36_sorted_nrows,j) = s36_sorted(j:j*s36_sorted_nrows);
   else
   s36_sorted_matrix(1:s36_sorted_nrows,j) = s36_sorted(s36_sorted_nrows*(j-
1)+1:j*s36_sorted_nrows);
   end
end

%arrange t38_orph according to adult survival values

for i=1:nsample
   if LHS_DRAWS(i,10) <= s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1)
& LHS_DRAWS(i,9) <= s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %1
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_11:nsample),1,'Replace',false); %1

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %2
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_10:cutoff_2_11),1,'Replace',false); %2

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %3
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %3

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %4
```

```
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_10:cutoff_2_11),1,'Replace',false); %4

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %5
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %5

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %6
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %6

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %7
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_10:cutoff_2_11),1,'Replace',false); %7

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %8
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %8

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %9
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %9
```

```
   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %10
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %10

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %11
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %11

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %12
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %12

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %13
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %13

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %14
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %14
```

```
   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %15
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %15

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %16
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %16

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %17
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %17

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %18
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %18

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %19
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %19
```

```
   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %20
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %20

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %21
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %21

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %22
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %22

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %23
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %23

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %24
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %24
```

```
   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %25
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %25

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %26
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %26

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %27
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %27

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %28
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %28

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %29
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %29

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1); %30
```

```
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %30

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %31
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_10:cutoff_2_11),1,'Replace',false); %31

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %32
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %32

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %33
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %33

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %34
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %34

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %35
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```
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %35

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %36
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %36

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %37
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %37

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %38
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %38

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %39
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %39

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
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```
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %40
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %40

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %41
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %41

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %42
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %42

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %43
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %43

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %44
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %44
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   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %45
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %45

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %46
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %46

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %47
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %47

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %48
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %48

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
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s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %49
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %49

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %50
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %50

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %51
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %51

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %52
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %52

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %53
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %53
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   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %54
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %54

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %55
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %55

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %56
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %56

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %57
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %57

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %58
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %58
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   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %59
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %59

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2); %60
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %60

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %61
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_9:cutoff_2_10),1,'Replace',false); %61

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %62
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %62

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %63
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %63
```

```
   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %64
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %64

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %65
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %65

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %66
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %66

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %67
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %67

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %68
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %68
```

```
   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %69
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %69

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %70
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %70

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2)& LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %71
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %71

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %72
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %72

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
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s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %73
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %73

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %74
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %74

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %75
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %75

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %76
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %76

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %77
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %77
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   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %78
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %78

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %79
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %79

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %80
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %80

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %81
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %81

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
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s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %82
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %82

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %83
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %83

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %84
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %84

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %85
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %85

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %86
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %86

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
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s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %87
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %87

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %88
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %88

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %89
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %89

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3); %90
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %90

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %91
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_8:cutoff_2_9),1,'Replace',false); %91

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
```

```
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %92
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %92

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %93
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %93

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %94
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %94

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %95
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %95

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %96
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %96

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
```

```
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %97
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %97

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %98
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %98

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %99
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %99

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %100
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %100

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %101
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %101
```

```
   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %102
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %102

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %103
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %103

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %104
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %104

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %105
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %105

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
```

```
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %106
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %106

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %107
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %107

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %108
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %108

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %109
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %109

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %110
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %110
```

```
   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %111
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %111

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %112
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %112

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %113
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %113

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %114
       LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %114

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %115
```

```
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %115

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %116
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %116

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %117
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %117

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %118
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %118

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %119
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %119

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %120
```

```
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_1:cutoff_2_2),1,'Replace',false); %120

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %121
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_7:cutoff_2_8),1,'Replace',false); %121

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %122
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %122

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %123
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %123

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %124
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %124

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16)
<= s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %125
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %125

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) <=
```

```
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %126
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %126

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %127
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_6:cutoff_2_7),1,'Replace',false); %127

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %128
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %128

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %129
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %129

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %130
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %130

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
```

```
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %131
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %131

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),1) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %132
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %132

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %133
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_5:cutoff_2_6),1,'Replace',false); %133

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %134
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %134

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %135
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %135

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
```

```
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %136
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %136

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %137
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %137

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),2) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %138
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %138

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %139
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_4:cutoff_2_5),1,'Replace',false); %139

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %140
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %140

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
```

```
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %141
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %141

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %142
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %142

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %143
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %143

   elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),3) & LHS_DRAWS(i,16) <=
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %144
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_1:cutoff_2_2),1,'Replace',false); %144

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %145
      LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_3:cutoff_2_4),1,'Replace',false); %145

   elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %146
```

```
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %146

    elseif LHS_DRAWS(i,10) <=
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %147
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_1:cutoff_2_2),1,'Replace',false); %147

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) <=
s918_sorted(cutoff_1) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %148
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_2:cutoff_2_3),1,'Replace',false); %148

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_1) & LHS_DRAWS(i,9) <= s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %149
        LHS_DRAWS(i,8) =
datasample(t38_orph_sorted(cutoff_2_1:cutoff_2_2),1,'Replace',false); %149

    elseif LHS_DRAWS(i,10) >
s918orph_sorted_matrix((nsample/s918orph_sorted_ncolumns),1) & LHS_DRAWS(i,9) >
s918_sorted(cutoff_2) & LHS_DRAWS(i,16) >
s1935_sorted_matrix((nsample/s1935_sorted_ncolumns),4) & LHS_DRAWS(i,19) >
s36_sorted_matrix((nsample/s36_sorted_ncolumns),4); %150
        LHS_DRAWS(i,8) = datasample(t38_orph_sorted(1:cutoff_2_1),1,'Replace',false); %150

    end

end

%change t918_orph column so that it correlates with adult survival

t918_orph_sorted = sort(LHS_DRAWS(:,13)); %sort t918_orph values
uneven_divisor_3 = 9; %nsample not divisible by 9
cutoff_3_1 = round(nsample/uneven_divisor_3);
cutoff_3_2 = round((nsample/uneven_divisor_3)*2);
cutoff_3_3 = round((nsample/uneven_divisor_3)*3);
cutoff_3_4 = round((nsample/uneven_divisor_3)*4);
```

```
cutoff_3_5 = round((nsample/uneven_divisor_3)*5);
cutoff_3_6 = round((nsample/uneven_divisor_3)*6);
cutoff_3_7 = round((nsample/uneven_divisor_3)*7);
cutoff_3_8 = round((nsample/uneven_divisor_3)*8);

%arrange t918_orph according to adult survival values

for i=1:nsample
   if LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,19) <= s36_sorted_matrix(s36_sorted_nrows,1); %1
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_8:nsample),1,'Replace',false); %1

   elseif LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,2) %2
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_7:cutoff_3_8),1,'Replace',false); %2

   elseif LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,3); %3
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_6:cutoff_3_7),1,'Replace',false); %3

   elseif LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,4); %4
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_5:cutoff_3_6),1,'Replace',false); %4

   elseif LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,4); %5
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_4:cutoff_3_5),1,'Replace',false); %5

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,1); %6
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_7:cutoff_3_8),1,'Replace',false); %6

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,2) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,2) %7
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```
        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_6:cutoff_3_7),1,'Replace',false); %7

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,2) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,3); %8
        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_5:cutoff_3_6),1,'Replace',false); %8

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,2) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,4); %9
        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_4:cutoff_3_5),1,'Replace',false); %9

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,1) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,2) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,4); %10
        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_3:cutoff_3_4),1,'Replace',false); %10

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,2) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,1); %11
        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_6:cutoff_3_7),1,'Replace',false); %11

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,2) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,3) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,2) %12
        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_5:cutoff_3_6),1,'Replace',false); %12

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,2) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,3) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,3); %13

        LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_4:cutoff_3_5),1,'Replace',false); %13

    elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,2) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,3) & LHS_DRAWS(i,19) >
```

```
s36_sorted_matrix(s36_sorted_nrows,3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,4); %14

      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_3:cutoff_3_4),1,'Replace',false); %14

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,2) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,3) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,4); %15
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_2:cutoff_3_3),1,'Replace',false); %15

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,3) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,4) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,1); %16
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_5:cutoff_3_6),1,'Replace',false); %16

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,3) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,4) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,2) %17
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_4:cutoff_3_5),1,'Replace',false); %17

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,3) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,4) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,3); %18

      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_3:cutoff_3_4),1,'Replace',false); %18

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,3) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,4) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,4); %19

      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_2:cutoff_3_3),1,'Replace',false); %19

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,3) &
LHS_DRAWS(i,16) <= s1935_sorted_matrix(s1935_sorted_nrows,4) & LHS_DRAWS(i,19) >
s36_sorted_matrix(s36_sorted_nrows,4); %20
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_1:cutoff_3_2),1,'Replace',false); %20
```

```
   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,4) &
LHS_DRAWS(i,19) <= s36_sorted_matrix(s36_sorted_nrows,1); %21
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_4:cutoff_3_5),1,'Replace',false); %21

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,4) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,1) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,2) %22
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_3:cutoff_3_4),1,'Replace',false); %22

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,4) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,2) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,3); %23
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_2:cutoff_3_3),1,'Replace',false); %23

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,4) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,3) & LHS_DRAWS(i,19) <=
s36_sorted_matrix(s36_sorted_nrows,4); %24
      LHS_DRAWS(i,13) =
datasample(t918_orph_sorted(cutoff_3_1:cutoff_3_2),1,'Replace',false); %24

   elseif LHS_DRAWS(i,16) > s1935_sorted_matrix(s1935_sorted_nrows,4) &
LHS_DRAWS(i,19) > s36_sorted_matrix(s36_sorted_nrows,4); %25
      LHS_DRAWS(i,13) = datasample(t918_orph_sorted(1:cutoff_3_1),1,'Replace',false); %25
   end

end

corr_check = corr(LHS_DRAWS);

%filename = 'draw_corrs.xlsx';

%writematrix(corr_check,filename);
```

LHS_matrices

```
beta_parameters;
%beta_parameters_less_poaching;
%beta_parameters_more_poaching;
%beta_parameters_irr;
LHS_draws;

nstages = 8;

LHS_MATRICES = zeros(nstages,nstages,nsample);

for k = 1:nsample
   LHS_MATRICES(1,1,:) = LHS_DRAWS(:,1).*(1-LHS_DRAWS(:,2)-LHS_DRAWS(:,3));
   LHS_MATRICES(1:8,2,:) = 0;
   LHS_MATRICES(1,3:4,:) = 0;
   LHS_MATRICES(1,5,:) = LHS_DRAWS(:,14).*LHS_DRAWS(:,9).*(1-
LHS_DRAWS(:,11)-LHS_DRAWS(:,13));
   LHS_MATRICES(1,6,:) = LHS_DRAWS(:,15).*LHS_DRAWS(:,10).*(1-
LHS_DRAWS(:,12));
   LHS_MATRICES(1,7,:) = LHS_DRAWS(:,16).*LHS_DRAWS(:,18).*(1-
LHS_DRAWS(:,17));
   LHS_MATRICES(1,8,:) = LHS_DRAWS(:,20).*LHS_DRAWS(:,19);
   LHS_MATRICES(2,1,:) = LHS_DRAWS(:,3).*0;
   LHS_MATRICES(2,3:8,:) = 0;
   LHS_MATRICES(3,1,:) = LHS_DRAWS(:,2).*LHS_DRAWS(:,1);
   LHS_MATRICES(3,3,:) = LHS_DRAWS(:,4).*(1-LHS_DRAWS(:,6)-LHS_DRAWS(:,8));
   LHS_MATRICES(3,4:8,:) = 0;
   LHS_MATRICES(4:8,1,:) = 0;
   LHS_MATRICES(4,3,:) = LHS_DRAWS(:,8).*LHS_DRAWS(:,5);
   LHS_MATRICES(4,4,:) = LHS_DRAWS(:,5).*(1-LHS_DRAWS(:,7));
   LHS_MATRICES(4,5:8,:) = 0;
   LHS_MATRICES(5,3,:) = LHS_DRAWS(:,6).*LHS_DRAWS(:,4);
   LHS_MATRICES(5,4,:) = 0;
   LHS_MATRICES(5,5,:) = LHS_DRAWS(:,9).*(1-LHS_DRAWS(:,11)-LHS_DRAWS(:,13));
   LHS_MATRICES(5,6:8,:) = 0;
   LHS_MATRICES(6:8,3,:) = 0;
   LHS_MATRICES(6,4,:) = LHS_DRAWS(:,7).*LHS_DRAWS(:,5);
   LHS_MATRICES(6,5,:) = LHS_DRAWS(:,13).*LHS_DRAWS(:,10);
   LHS_MATRICES(6,6,:) = LHS_DRAWS(:,10).*(1-LHS_DRAWS(:,12));
   LHS_MATRICES(6,7:8,:) = 0;
   LHS_MATRICES(7:8,4,:) = 0;
   LHS_MATRICES(7,5,:) = LHS_DRAWS(:,9).*LHS_DRAWS(:,11);
   LHS_MATRICES(7,6,:) = LHS_DRAWS(:,10).*LHS_DRAWS(:,12);
   LHS_MATRICES(7,7,:) = LHS_DRAWS(:,16).*(1-LHS_DRAWS(:,17));
   LHS_MATRICES(7,8,:) = 0;
```

```
   LHS_MATRICES(8,5:6,:) = 0;
   LHS_MATRICES(8,7,:) = LHS_DRAWS(:,17).*LHS_DRAWS(:,16);
   LHS_MATRICES(8,8,:) = LHS_DRAWS(:,19);
end

%irreducible
% for k = 1:nsample
%    LHS_MATRICES(1,1,:) = LHS_DRAWS(:,1).*(1-LHS_DRAWS(:,2)-LHS_DRAWS(:,3));
%    LHS_MATRICES(1,2:8,:) = 0;
%    LHS_MATRICES(1,3:4,:) = 0;
%    LHS_MATRICES(1,5,:) = LHS_DRAWS(:,14).*LHS_DRAWS(:,9).*(1-
LHS_DRAWS(:,11)-LHS_DRAWS(:,13));
%    LHS_MATRICES(1,6,:) = LHS_DRAWS(:,15).*LHS_DRAWS(:,10).*(1-
LHS_DRAWS(:,12));
%    LHS_MATRICES(1,7,:) = LHS_DRAWS(:,16).*LHS_DRAWS(:,18).*(1-
LHS_DRAWS(:,17));
%    LHS_MATRICES(1,8,:) = LHS_DRAWS(:,20).*LHS_DRAWS(:,19);
%    LHS_MATRICES(2,1,:) = LHS_DRAWS(:,3).*LHS_DRAWS(:,21);
%    LHS_MATRICES(2,2,:) = LHS_DRAWS(:,21).*(1-LHS_DRAWS(:,22));
%    LHS_MATRICES(2,3:8,:) = 0;
%    LHS_MATRICES(3,1,:) = LHS_DRAWS(:,2).*LHS_DRAWS(:,1);
%    LHS_MATRICES(3,2,:) = 0;
%    LHS_MATRICES(3,3,:) = LHS_DRAWS(:,4).*(1-LHS_DRAWS(:,6)-LHS_DRAWS(:,8));
%    LHS_MATRICES(3,4:8,:) = 0;
%    LHS_MATRICES(4:8,1,:) = 0;
%    LHS_MATRICES(4,2,:) = LHS_DRAWS(:,21).*LHS_DRAWS(:,22);
%    LHS_MATRICES(4,3,:) = LHS_DRAWS(:,8).*LHS_DRAWS(:,5);
%    LHS_MATRICES(4,4,:) = LHS_DRAWS(:,5).*(1-LHS_DRAWS(:,7));
%    LHS_MATRICES(4,5:8,:) = 0;
%    LHS_MATRICES(5:8,2,:) = 0;
%    LHS_MATRICES(5,3,:) = LHS_DRAWS(:,6).*LHS_DRAWS(:,4);
%    LHS_MATRICES(5,4,:) = 0;
%    LHS_MATRICES(5,5,:) = LHS_DRAWS(:,9).*(1-LHS_DRAWS(:,11)-
LHS_DRAWS(:,13));
%    LHS_MATRICES(5,6:8,:) = 0;
%    LHS_MATRICES(6:8,3,:) = 0;
%    LHS_MATRICES(6,4,:) = LHS_DRAWS(:,7).*LHS_DRAWS(:,5);
%    LHS_MATRICES(6,5,:) = LHS_DRAWS(:,13).*LHS_DRAWS(:,10);
%    LHS_MATRICES(6,6,:) = LHS_DRAWS(:,10).*(1-LHS_DRAWS(:,12));
%    LHS_MATRICES(6,7:8,:) = 0;
%    LHS_MATRICES(7:8,4,:) = 0;
%    LHS_MATRICES(7,5,:) = LHS_DRAWS(:,9).*LHS_DRAWS(:,11);
%    LHS_MATRICES(7,6,:) = LHS_DRAWS(:,10).*LHS_DRAWS(:,12);
%    LHS_MATRICES(7,7,:) = LHS_DRAWS(:,16).*(1-LHS_DRAWS(:,17));
%    LHS_MATRICES(7,8,:) = 0;
%    LHS_MATRICES(8,5:6,:) = 0;
```

```
%     LHS_MATRICES(8,7,:) = LHS_DRAWS(:,17).*LHS_DRAWS(:,16);
%     LHS_MATRICES(8,8,:) = LHS_DRAWS(:,19);
% end
```

linear_regression

```
rng(10)

beta_parameters;
LHS_draws;
LHS_matrices;
eigenvalues;

y = EIGENVALUES(:,1);
X = [LHS_DRAWS(:,1), LHS_DRAWS(:,2), LHS_DRAWS(:,3), LHS_DRAWS(:,4),
LHS_DRAWS(:,5), LHS_DRAWS(:,6), LHS_DRAWS(:,7), LHS_DRAWS(:,8),
LHS_DRAWS(:,9), LHS_DRAWS(:,10), LHS_DRAWS(:,11), LHS_DRAWS(:,12),
LHS_DRAWS(:,13), LHS_DRAWS(:,14), LHS_DRAWS(:,15), LHS_DRAWS(:,16),
LHS_DRAWS(:,17), LHS_DRAWS(:,18), LHS_DRAWS(:,19), LHS_DRAWS(:,20)];

yNorm = normalize(y);
XNorm = normalize(X, 1);

reg = fitlm(X, y);
regNorm = fitlm(XNorm, yNorm);

%visualize results

plotEffects(regNorm);

%check variable inflation factors
vif(XNorm) %Vasilaky, D. (2016) vif(X). MatLab Central File Exchange.
<mathwords.com/matlabcentral/fileexchange/60551-vif-x.>

%create table of results

RESULTS = regNorm.Coefficients(:,1);

rowNames = {'intercept';'s02'; 't02_38'; 't02_orph'; 's38'; 's38orph'; 't38_918'; 't38orph_918orph';
't38_orph';'s918';'s918orph';'t918_1935';'t918orph_1935';'t918_orph';'f918';'f918orph';'s1935';'t19
35_36';'f1935';'s36';'f36'};
colNames = {'Coefficient Estimate'};
RESULTS.Properties.RowNames = rowNames;
RESULTS.Properties.VariableNames = colNames;

%Write results to excel

filename = 'overall_linear_reg_results.csv';
writetable(RESULTS,filename,'WriteRowNames',true)
```

linear_regression_less_poaching

```
rng(2)

beta_parameters_less_poaching;
LHS_draws;
LHS_matrices;
eigenvalues;

y = EIGENVALUES(:,1);
X = [LHS_DRAWS(:,1), LHS_DRAWS(:,2), LHS_DRAWS(:,3), LHS_DRAWS(:,4),
LHS_DRAWS(:,5), LHS_DRAWS(:,6), LHS_DRAWS(:,7), LHS_DRAWS(:,8),
LHS_DRAWS(:,9), LHS_DRAWS(:,10), LHS_DRAWS(:,11), LHS_DRAWS(:,12),
LHS_DRAWS(:,13), LHS_DRAWS(:,14), LHS_DRAWS(:,15), LHS_DRAWS(:,16),
LHS_DRAWS(:,17), LHS_DRAWS(:,18), LHS_DRAWS(:,19), LHS_DRAWS(:,20)];

yNorm = normalize(y);
XNorm = normalize(X, 1);

reg = fitlm(X, y);
regNorm = fitlm(XNorm, yNorm);

%visualize results

plotEffects(regNorm);

%create table of results

RESULTS = regNorm.Coefficients(:,1);

rowNames = {'intercept';'s02'; 't02_38'; 't02_orph'; 's38'; 's38orph'; 't38_918'; 't38orph_918orph';
't38_orph';'s918';'s918orph';'t918_1935';'t918orph_1935';'t918_orph';'f918';'f918orph';'s1935';'t19
35_36';'f1935';'s36';'f36'};
colNames = {'Coefficient Estimate'};
RESULTS.Properties.RowNames = rowNames;
RESULTS.Properties.VariableNames = colNames;

%Write results to excel

filename = 'low_linear_reg_results.csv';
writetable(RESULTS,filename,'WriteRowNames',true)
```

linear_regression_more_poaching

```
rng(30)

beta_parameters_more_poaching;
LHS_draws;
LHS_matrices;
eigenvalues;

y = EIGENVALUES(:,1);
X = [LHS_DRAWS(:,1), LHS_DRAWS(:,2), LHS_DRAWS(:,3), LHS_DRAWS(:,4),
LHS_DRAWS(:,5), LHS_DRAWS(:,6), LHS_DRAWS(:,7), LHS_DRAWS(:,8),
LHS_DRAWS(:,9), LHS_DRAWS(:,10), LHS_DRAWS(:,11), LHS_DRAWS(:,12),
LHS_DRAWS(:,13), LHS_DRAWS(:,14), LHS_DRAWS(:,15), LHS_DRAWS(:,16),
LHS_DRAWS(:,17), LHS_DRAWS(:,18), LHS_DRAWS(:,19), LHS_DRAWS(:,20)];

yNorm = normalize(y);
XNorm = normalize(X, 1);

reg = fitlm(X, y);
regNorm = fitlm(XNorm, yNorm);


%visualize results

plotEffects(regNorm);

%create table of results

RESULTS = regNorm.Coefficients(:,1);

rowNames = {'intercept';'s02'; 't02_38'; 't02_orph'; 's38'; 's38orph'; 't38_918'; 't38orph_918orph';
't38_orph';'s918';'s918orph';'t918_1935';'t918orph_1935';'t918_orph';'f918';'f918orph';'s1935';'t19
35_36';'f1935';'s36';'f36'};
colNames = {'Coefficient Estimate'};
RESULTS.Properties.RowNames = rowNames;
RESULTS.Properties.VariableNames = colNames;

%Write results to excel

filename = 'high_linear_reg_results.csv';
writetable(RESULTS,filename,'WriteRowNames',true)
```

APPENDIX 4: Correlation matrix for Chapter 2

Supplementary Table A3: Correlations among parameters used in the sensitivity analysis of Chapter 2. The correlations we induced among orphaning rates and adult female survival rates are highlighted. See also Supplementary Table A4.

Rates	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. s02	1.00	-0.01	-0.01	0.01	-0.02	-0.02	0.01	-0.01	0.00	0.00	0.00	-0.01	-0.01	-0.02	-0.01	0.01	0.01	-0.02	0.01	0.01
2. t02	-0.01	1.00	0.00	0.01	-0.01	0.01	-0.01	0.00	0.02	0.01	-0.01	-0.02	0.01	0.01	-0.01	0.00	0.01	0.00	-0.02	-0.01
3. z02	-0.01	0.00	1.00	0.00	0.01	-0.01	0.01	0.84	-0.42	-0.23	-0.01	-0.01	0.60	0.00	0.00	-0.43	0.01	0.01	-0.41	0.02
4. s38	0.01	0.01	0.00	1.00	-0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	-0.01	0.01	0.02	-0.01	-0.01	0.01
5. v38	-0.02	-0.01	0.01	-0.01	1.00	0.02	0.00	0.01	0.00	0.00	-0.01	0.00	0.01	0.01	0.01	-0.02	-0.01	0.00	0.00	0.00
6. t38	-0.02	0.01	-0.01	0.01	0.02	1.00	-0.01	-0.01	0.00	-0.01	0.01	0.00	-0.01	0.01	-0.01	0.01	0.00	0.01	0.01	0.01
7. u38	0.01	-0.01	0.01	0.00	0.00	-0.01	1.00	0.01	-0.02	-0.01	-0.01	0.01	0.01	-0.01	-0.02	0.01	0.00	0.00	0.00	-0.01
8. z38	-0.01	0.00	0.84	0.00	0.01	-0.01	0.01	1.00	-0.30	-0.18	0.00	-0.02	0.83	0.00	0.00	-0.55	0.01	0.01	-0.55	0.01
9. s918	0.00	0.02	-0.42	0.00	0.00	0.00	-0.02	-0.30	1.00	0.01	0.00	0.01	0.00	0.01	0.00	0.02	0.00	0.00	-0.02	-0.01
10. v918	0.00	0.01	-0.23	0.01	0.00	-0.01	-0.01	-0.18	0.01	1.00	0.01	0.02	-0.01	0.02	0.02	0.00	0.00	-0.01	0.00	-0.01
11. t918	0.00	-0.01	-0.01	0.00	-0.01	0.01	-0.01	0.00	0.00	0.01	1.00	0.01	0.00	-0.01	0.00	0.01	0.01	0.00	0.00	-0.01
12. u918	-0.01	-0.02	-0.01	0.00	0.00	0.00	0.01	-0.02	0.01	0.02	0.01	1.00	-0.01	0.00	0.00	-0.02	-0.01	0.02	0.02	-0.01
13. z918	-0.01	0.01	0.60	0.00	0.01	-0.01	0.01	0.83	0.00	-0.01	0.00	-0.01	1.00	0.00	0.00	-0.59	0.01	0.02	-0.60	0.00
14. f918	-0.02	0.01	0.00	0.00	0.01	0.01	-0.01	0.00	0.01	0.02	-0.01	0.00	0.00	1.00	0.01	0.01	0.00	-0.01	0.00	0.02
15. g918	-0.01	-0.01	0.00	-0.01	0.01	-0.01	-0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.01	1.00	0.00	0.00	0.02	-0.01	0.00
16. s1935	0.01	0.00	-0.43	0.01	-0.02	0.01	0.01	-0.55	0.02	0.00	0.01	-0.02	-0.59	0.01	0.00	1.00	0.00	-0.01	0.00	-0.01
17. t1935	0.01	0.01	0.01	0.02	-0.01	0.00	0.00	0.01	0.00	0.00	0.01	-0.01	0.01	0.00	0.00	0.00	1.00	0.01	-0.01	0.02
18. f1935	-0.02	0.00	0.01	-0.01	0.00	0.01	0.00	0.01	0.00	-0.01	0.00	0.02	0.02	-0.01	0.02	-0.01	0.01	1.00	-0.01	0.00
19. s >35	0.01	-0.02	-0.41	-0.01	0.00	0.01	0.00	-0.55	-0.02	0.00	0.00	0.02	-0.60	0.00	-0.01	0.00	-0.01	-0.01	1.00	-0.01
20. f >35	0.01	-0.01	0.02	0.01	0.00	0.01	-0.01	0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.02	0.00	-0.01	0.02	0.00	-0.01	1.00

Supplementary Table A4: Correlations observed in the data. Compare with correlations in Supplementary Table A3.

Correlated rates	Observed correlation
z02 orphaning and s 918	-0.47
z02 orphaning and v918orph	-0.32
z02 orphaning and s1935	-0.46
z02 orphaning and s>35	-0.50
z38 orphaning and s918	-0.54
z38 orphaning and v918orph	-0.32
z38 orphaning and s1935	-0.83
z38 orphaning and s>35	-0.80
z918 orphaning and s1935	-0.75
z918 orphaning and s>35	-0.78

APPENDIX 5: Non-monotonicity checks for Chapter 2

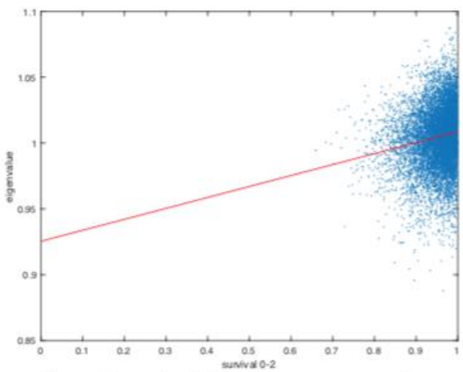


Figure 1: survival 0-2 years versus growth rate

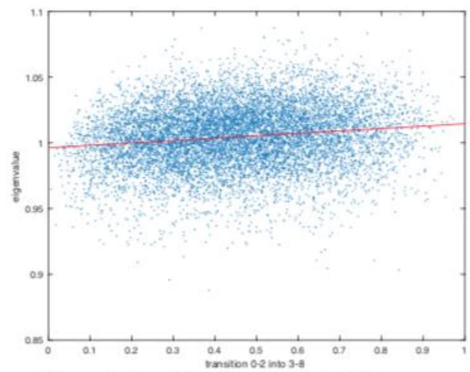


Figure 2: transition from 0-2 into 3-8 years versus growth rate

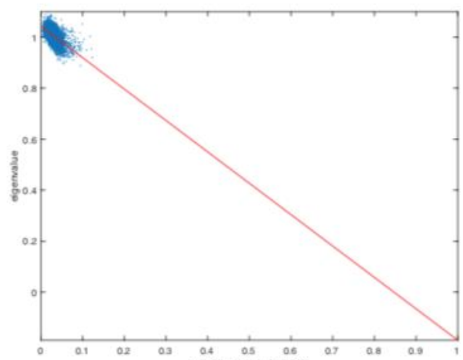


Figure 3: transition from 0-2 years into orphan versus growth rate

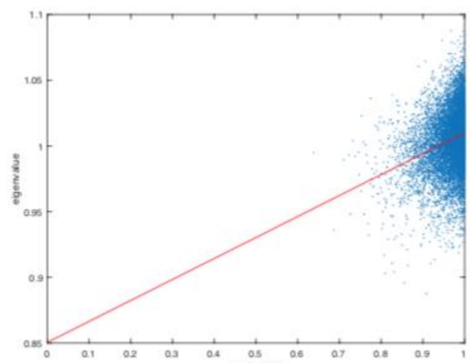


Figure 4: survival 3-8 years versus growth rate

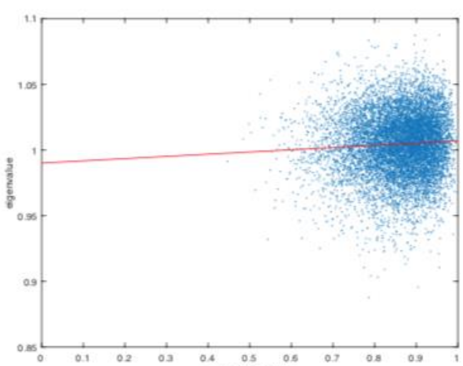


Figure 5: survival 3-8 orphan versus growth rate

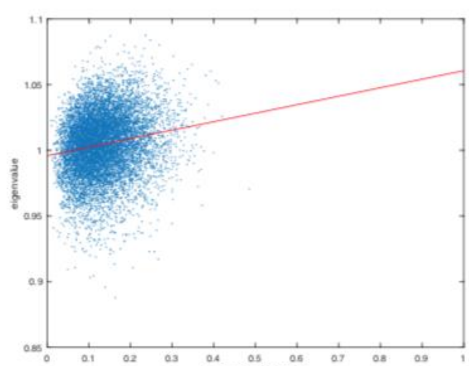


Figure 6: transition from 3-8 into 9-18 years versus growth rate

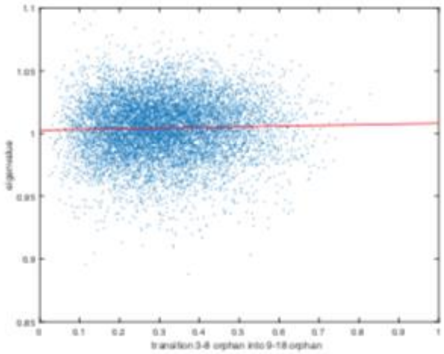


Figure 7: transition from 3-8 orphan into 9-18 orphan versus growth rate

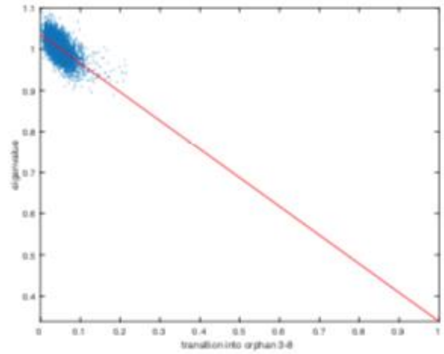


Figure 8: transition from 3-8 years into orphan versus growth rate

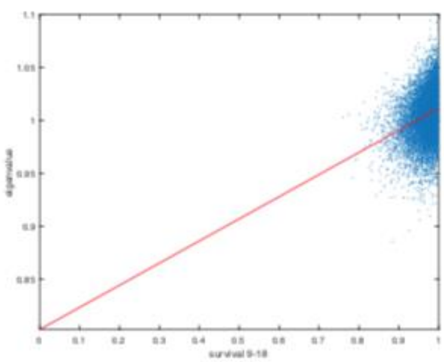


Figure 9: survival 9-18 years versus growth rate

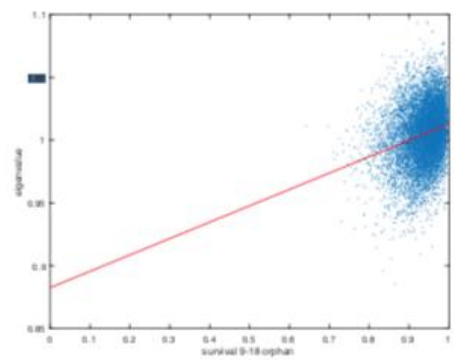


Figure 10: survival 9-18 orphan versus growth rate

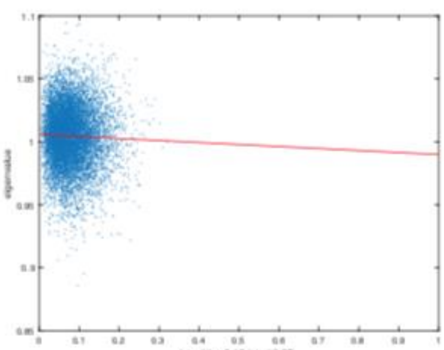


Figure 11: transition from 9-18 into 19-35 years versus growth rate

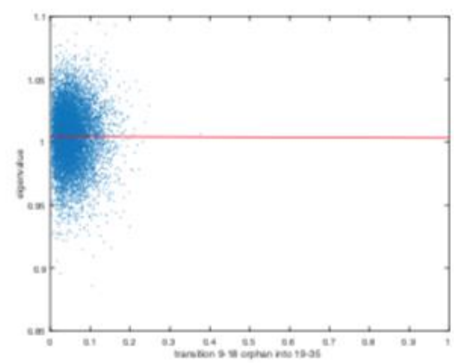


Figure 12: transition from 9-18 orphan into 19-35 years versus growth rate

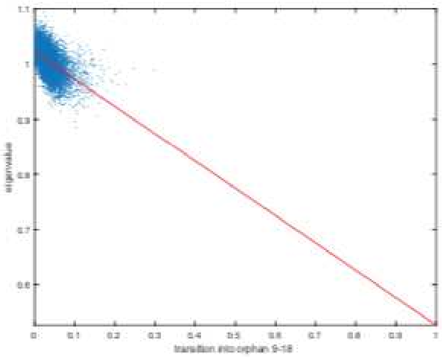


Figure 13: transition from 9-18 years into orphan versus growth rate

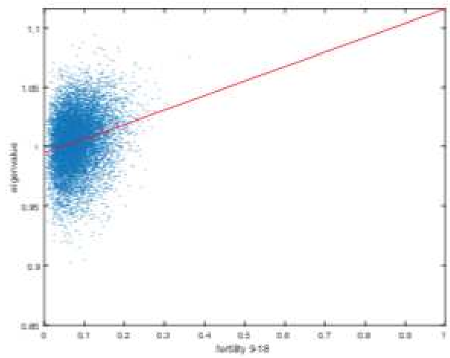


Figure 14: fertility 9-18 years versus growth rate

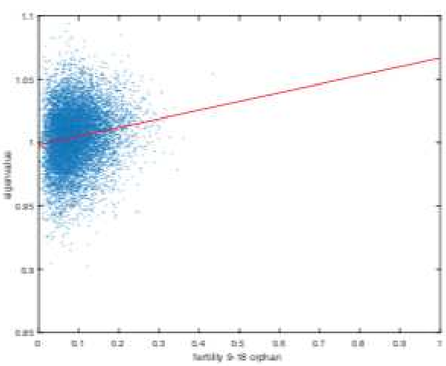


Figure 15: fertility 9-18 orphan versus growth rate

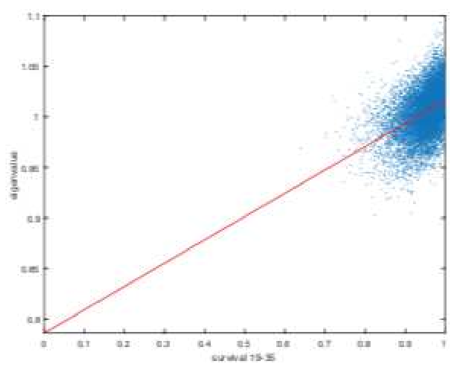


Figure 16: survival 19-35 years versus growth rate

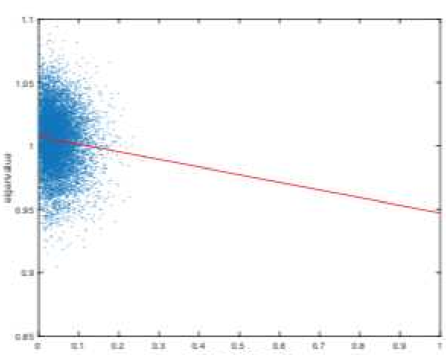


Figure 17: transition from 19-35 into >35 years versus growth rate

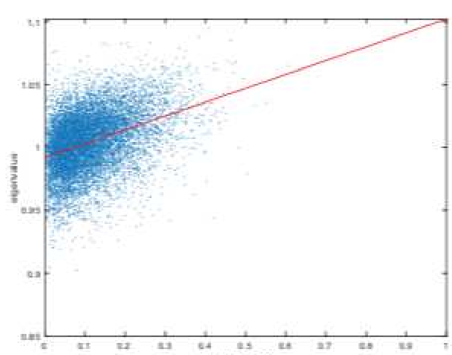


Figure 18: fertility 19-35 years versus growth rate

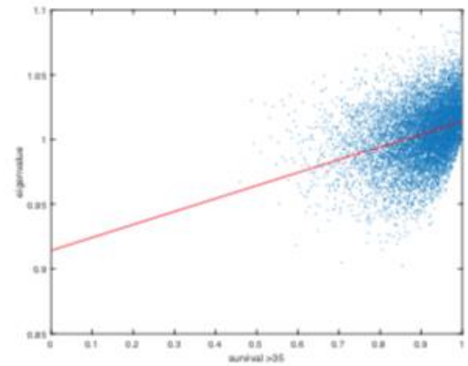


Figure 19: survival >35 years versus growth rate

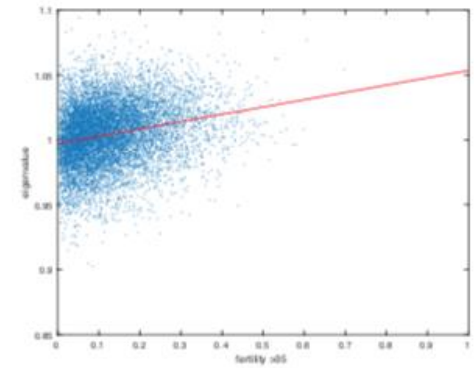


Figure 20: fertility >35 years versus growth rate

APPENDIX 6: Supplemental information for Chapter 3

Although Oduor *et al.* (2020) found GC secretion increased with age, age dropped out of our top model. This may be because we did not sample from a wide age range, given elephants can live to be greater than 60 years old in the wild (Supplementary Figure A4B). Differences between mature adults and young adults or calves may have been apparent if we had sampled from more coarsely separated age classes. Time of day showed an effect on GC levels in zoo elephants, with concentrations highest in the morning and lowest around midnight (Brown *et al.*, 2010). We did not sample across a large time range (Supplementary Figure A4C), and this could have obscured a similar effect in our study system. Zoo elephants may also have different diurnal rhythms than wild elephants after adjusting to human-driven schedules. The control variable of time on the ground prior to collection showed no effect, unsurprising because most samples were collected within 30 minutes and all samples within 2 hours, leaving little time for degradation (Supplementary Figure A4D).

We suspected the resolution provided by fine-scale information on strongylid fecal egg counts from the same dung boluses sampled for glucocorticoids would unveil a positive correlation with nematode parasite infection. However, we did not find support for a correlation of GC levels with strongylid FECs, agreeing with literature suggesting nematode parasites more rarely correlate with GC concentrations than other types of parasites (O'Dwyer *et al.*, 2020). The model without FECs outperformed the model with FECs after DIC selection, but only by one point (Supplementary Table A5). In the outperformed model, FECs showed a slight positive correlation with GC concentrations (Supplementary Figure A8). Interestingly, in this model the effect of being with a non-natal core group was weaker than in the top model. This may have simply been due to a lower overall sample size, but Parker *et al.* (2020) found that non-natal orphans have lower FECs, therefore including FECs might have drawn from variation due to non-natality if some of that variation was associated with lower strongylid infection.

Supplementary Table A5: Progression of model selection process, showing DIC scores, with asterisks next to the top models for sample set 1 (514 samples) and sample set 2 (464 samples).

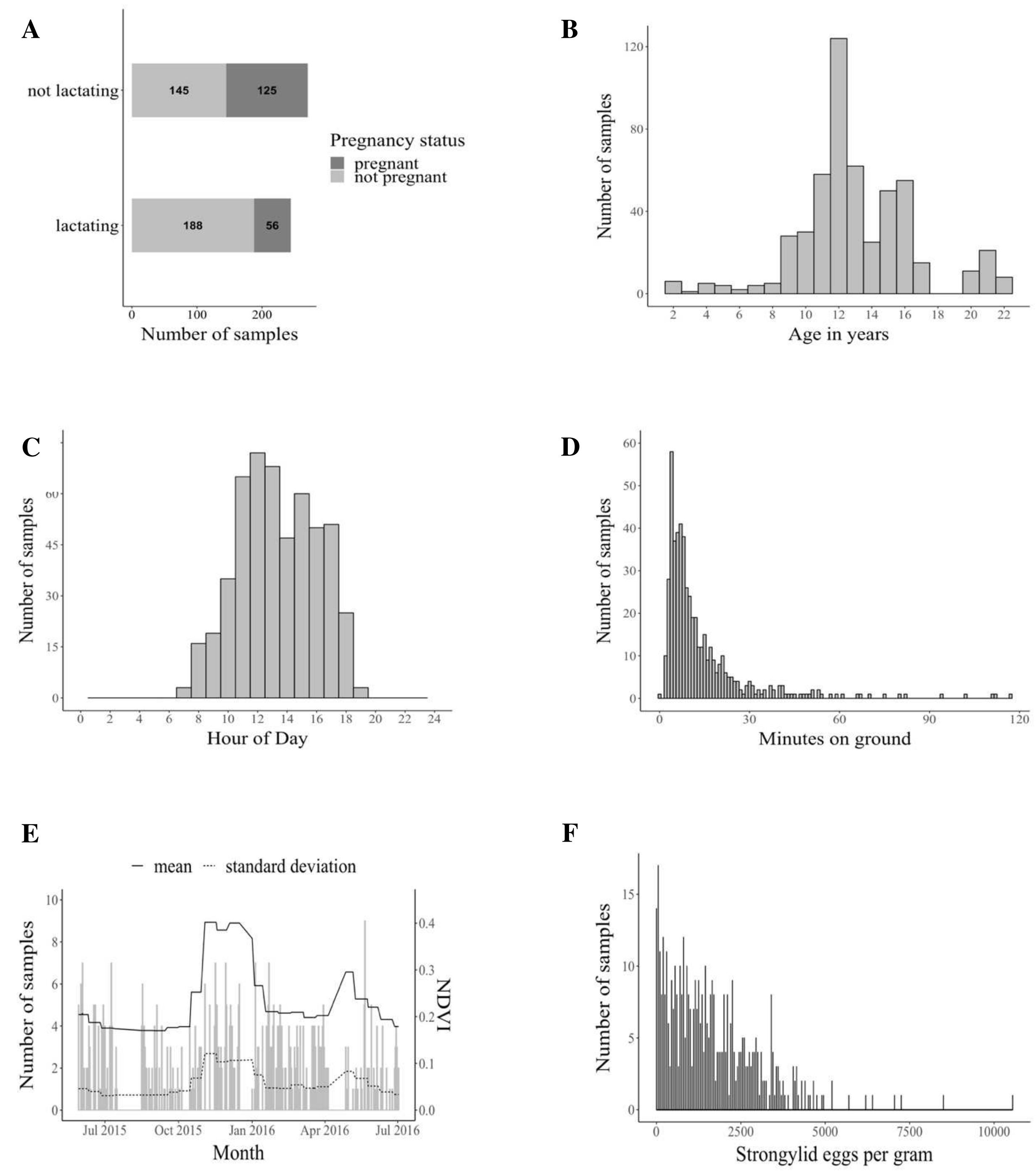
Model	Sample set	Variables	Description	Mean deviance	Penalty	Penalized Deviance
1	1	f+m+n+o+a+g+l+s+t+v+p+z	everything	1528	15.50	1544
2	1	m+n+o+a+g+l+s+t+v+p+z	everything – adult caregivers	1534	14.40	1549
3	1	f+n+o+a+g+l+s+t+v+p+z	everything – age mates	1539	14.10	1553
4	1	f+m+o+a+g+l+s+t+v+p+z	everything – number of samples	1541	14.15	1556
5	1	f+m+n+a+g+l+s+t+v+p+z	everything – orphan status	1528	14.16	1542
6	1	f+m+n+o+g+l+s+t+v+p+z	everything – with non-natal group	1533	14.10	1547
7	1	f+m+n+o+a+l+s+t+v+p+z	everything – age	1528	14.13	1542
8	1	f+m+n+o+a+g+s+t+v+p+z	everything – lactating	1528	14.16	1542
9	1	f+m+n+o+a+g+l+t+v+p+z	everything – time sat	1529	14.40	1543
10	1	f+m+n+o+a+g+l+s+v+p+z	everything – time of day	1528	14.10	1542
11	1	f+m+n+o+a+g+l+s+t+p+z	everything – ndvi	1540	14.17	1554
12	1	f+m+n+o+a+g+l+s+t+v+z	everything – pregnancy	1528	14.14	1543
13	1	f+m+n+o+a+g+l+s+t+v+p	everything – ndvi standard deviation	1543	14.17	1557
14	1	f+m+n+a+l+s+t+v+p+z	everything – orphan status – age	1528	13.16	1541
15	1	f+m+n+a+s+t+v+p+z	everything – orphan status – age – lactating	1529	12.10	1541
16	1	f+m+n+a+l+t+v+p+z	everything – orphan status – age – time sat	1528	12.14	1540
17	1	f+m+n+a+l+v+p+z	everything – orphan status – age – time sat – time of day	1528	11.14	1539
18*	1	f+m+n+a+l+v+z	everything – orphan status – age – time sat – time of day – pregnancy	1527	10.12	1537
19*	2	f+m+n+a+l+v+z+w	(everything – orphan status – age – time sat – time of day – pregnancy)	1387	11.13	1398
20	2	f+m+n+a+l+v+z	(everything – orphan status – age – time sat – time of day – pregnancy) – fecal egg counts	1387	10.12	1397

Supplementary Table A6: Results from the second-best model that included pregnancy.

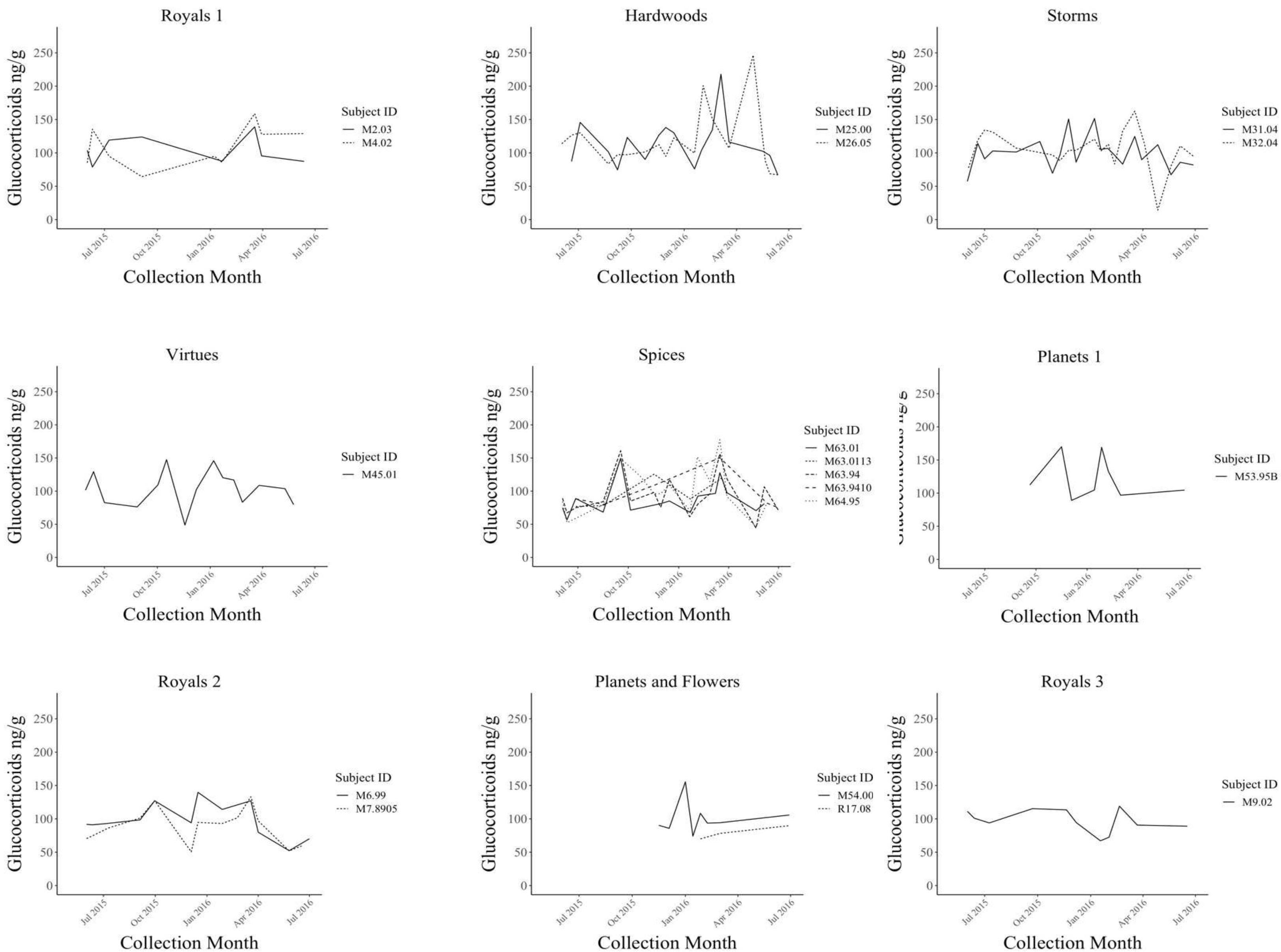
Coefficient	Covariate	Estimate	95% CI lower	95% CI upper
β_1	adult caregivers	-0.16	-0.26	-0.06
β_2	age mates	-0.16	-0.26	-0.06
β_3	number of samples	-0.18	-0.28	-0.09
β_5	with non-natal group	-0.44	-0.81	-0.06
γ_2	lactating	-0.14	-0.32	0.04
γ_5	mean NDVI	-0.87	-1.35	-0.39
γ_6	pregnancy	0.07	-0.12	0.25
γ_7	NDVI standard deviation	0.98	0.50	1.46

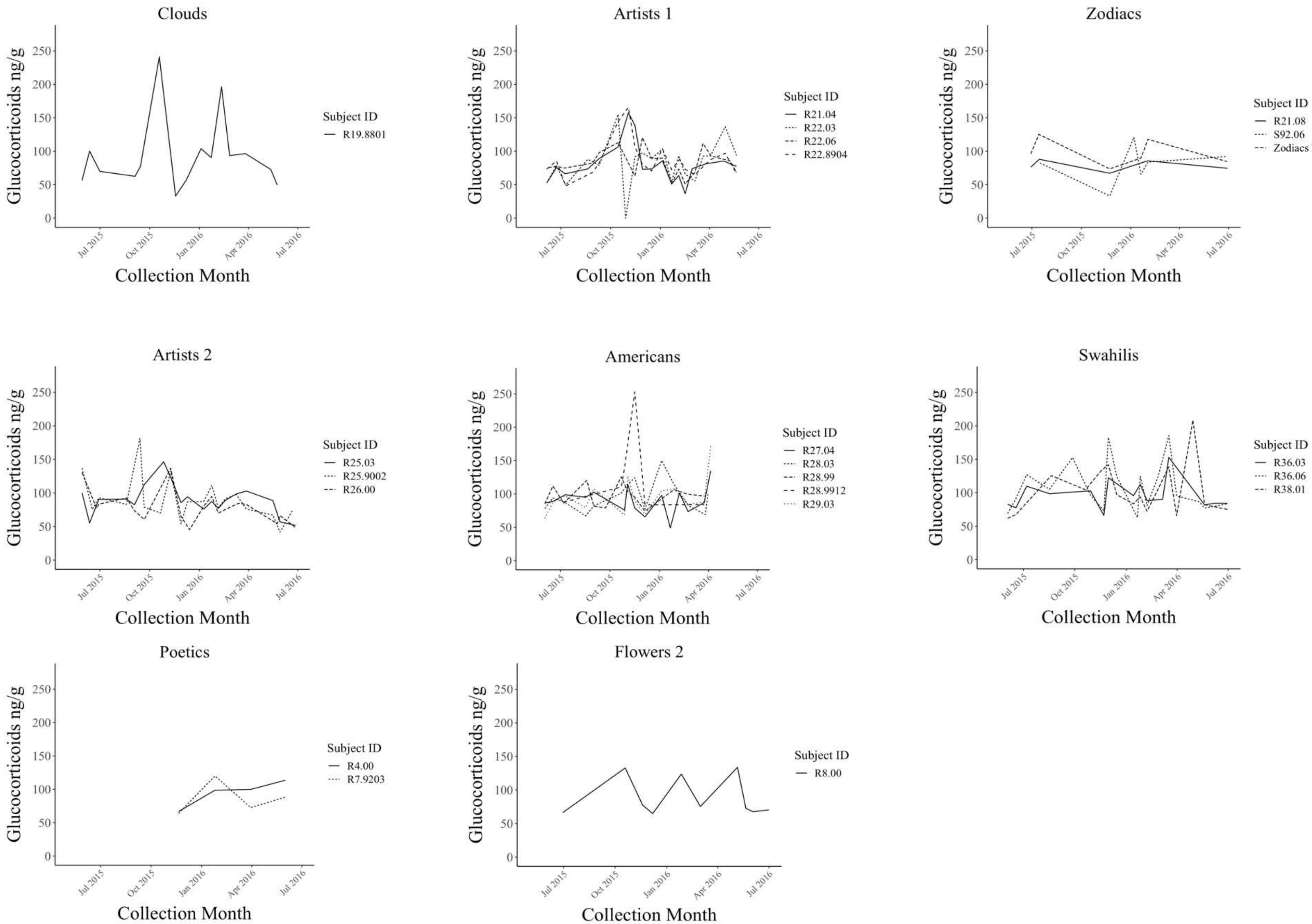
Supplementary Table A7: Results from the model run with fewer samples that included strongylid fecal egg counts.

Coefficient	Covariate	Estimate	95% CI lower	95% CI upper
β_1	adult caregivers	-0.16	-0.27	-0.06
β_2	age mates	-0.17	-0.27	-0.07
β_3	number of samples	-0.18	-0.28	-0.08
β_5	with non-natal group	-0.36	-0.75	0.02
γ_2	lactating	-0.14	-0.32	0.04
γ_5	mean NDVI	-1.04	-1.59	-0.49
γ_7	NDVI standard deviation	1.08	0.57	1.61
γ_8	strongylid fecal egg counts	0.05	-0.042	0.15

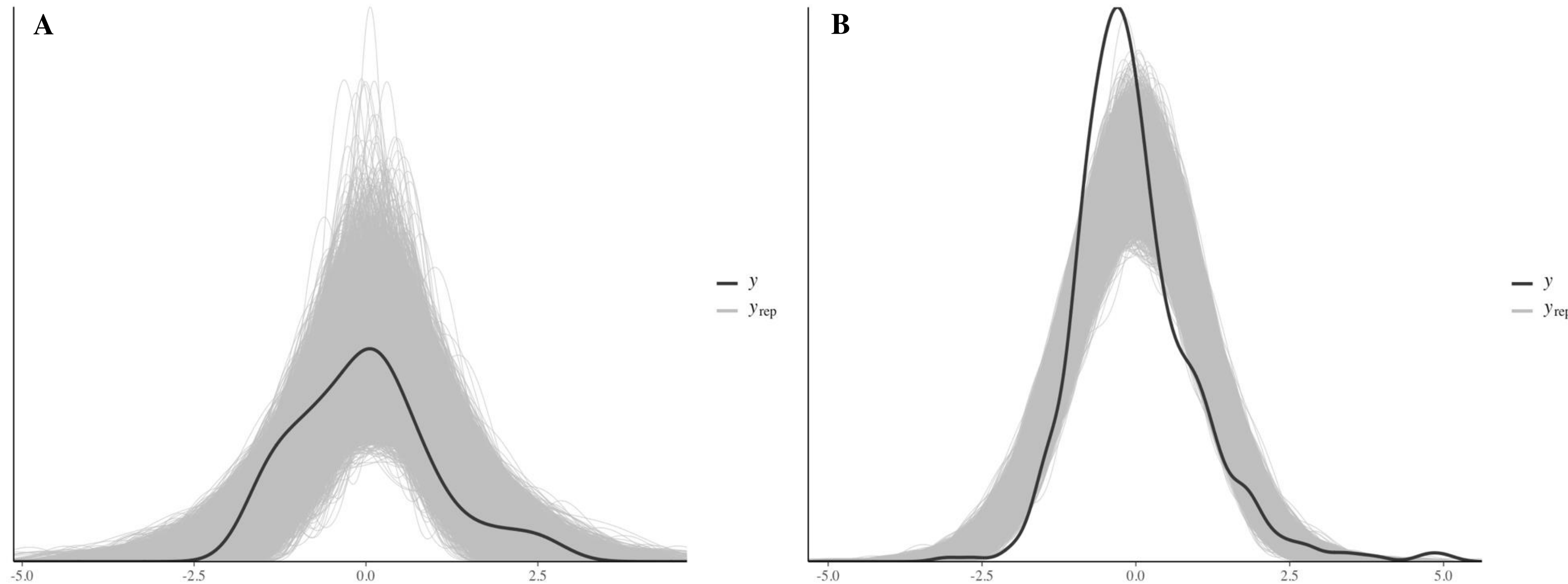


Supplementary Figure A4: Time-variant covariates. A) Bar chart showing number of samples collected from females who were lactating versus not, colored according to whether they were collected from pregnant versus not pregnant females. B-F) Histogram of samples according to age of the female they were collected from, time of day they were collected, amount of time spent on the ground prior to collection, month of collection (including lines showing corresponding mean and standard deviation of NDVI according to the secondary y-axis), and estimated number of strongylid eggs per gram of fecal matter from the same sampling event.

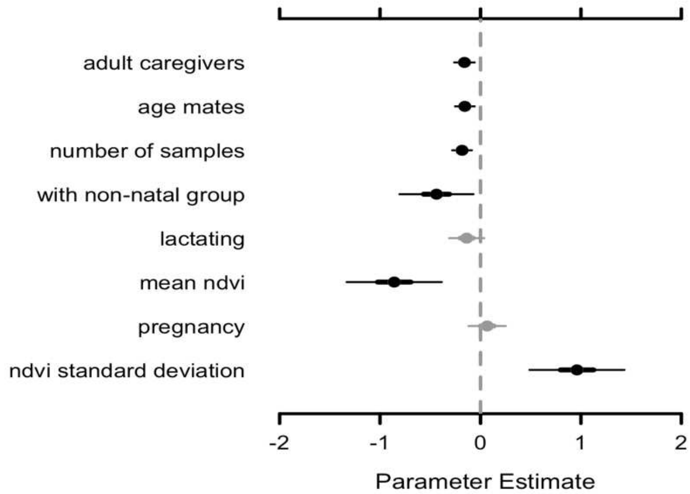

Royals 1
Subject ID
M2.03
M4.02
Hardwoods
Subject ID
M25.00
M26.05
Storms
Subject ID
M31.04
M32.04
Virtues
Subject ID
M45.01
Spices
Subject ID
M63.01
M63.0113
M63.94
M63.9410
M64.95
Planets 1
Subject ID
M53.95B
Royals 2
Subject ID
M6.99
M7.8905
Planets and Flowers
Subject ID
M54.00
R17.08
Royals 3
Subject ID
M9.02
Glucocorticoids ng/g
0
50
100
150
200
250
Collection Month
Jul 2015
Oct 2015
Jan 2016
Apr 2016
Jul 2016


Clouds
Artists 1
Zodiacs
Artists 2
Americans
Swahilis
Poetics
Flowers 2
Glucocorticoids ng/g
Collection Month
Jul 2015
Oct 2015
Jan 2016
Apr 2016
Jul 2016
Subject ID
R19.8801
R21.04
R22.03
R22.06
R22.8904
R21.08
S92.06
Zodiacs B
R25.03
R25.9002
R26.00
R27.04
R28.03
R28.99
R28.9912
R29.03
R36.03
R36.06
R38.01
R4.00
R7.9203
R8.00

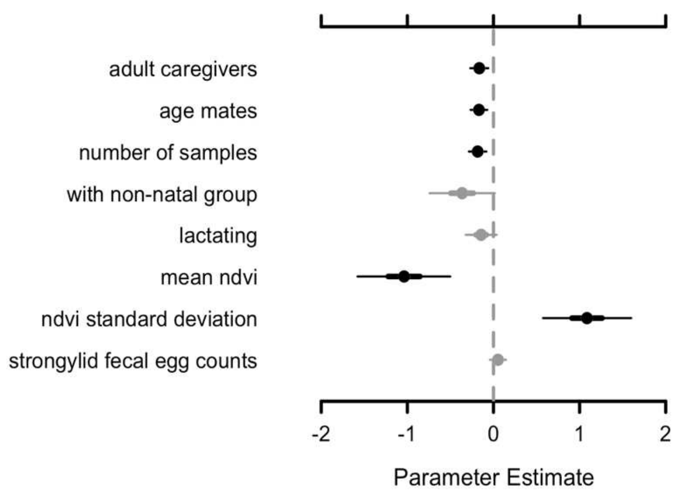
Supplementary Figure A5: Time series graphs showing each study subject's fecal glucocorticoid concentration from one sample to the next, with subjects organized according to core group.



Supplementary Figure A6: A) Graph of distribution for standardized average fecal glucocorticoid concentrations data in black, overlaying 10,000 simulations based on the top model in gray. B) Graph of distribution for standardized fecal glucocorticoid concentrations data across all samples in black, overlaying 10,000 simulation based on the top model in gray.



Supplementary Figure A7: Results from the second best model, with black denoting estimates whose 95% confidence interval did not overlap zero, and gray denoting estimates whose 50% confidence interval did not overlap zero.



Supplementary Figure A8: Results from the model run with fewer samples that included strongylid fecal egg counts, with black and filled circles denoting estimates whose 95% confidence interval did not overlap zero, and gray and filled circles denoting estimates whose 50% confidence interval did not overlap zero.

Global model specification Rjags code

```
model{
  #priors
  alpha ~ dnorm(0, .01)
  beta1 ~ dnorm(0, .01)
  beta2 ~ dnorm(0, .01)
  beta3 ~ dnorm(0, .01)
  beta4 ~ dnorm(0, .01)
  beta5 ~ dnorm(0, .01)
  gamma1 ~ dnorm(0, .01)
  gamma2 ~ dnorm(0, .01)
  gamma3 ~ dnorm(0, .01)
  gamma4 ~ dnorm(0, .01)
  gamma5 ~ dnorm(0, .01)
  gamma6 ~ dnorm(0, .01)
  gamma7 ~ dnorm(0, .01)
  tau1 ~ dgamma(.001,.001)
  tau2 ~ dgamma(.001,.001)
  sigma1 <- 1/sqrt(tau1)
  sigma2 <- 1/sqrt(tau2)

  #likelihoods
  for (i in 1:length(ID.Index)){
    mu1[i] <- alpha + beta1 * f[i] + beta2 * m[i] + beta3 * n[i] + beta4 * o[i] + beta5 * a[i]
    y_bar[i] ~ dnorm(mu1[i], tau1)
  }

  for (j in 1:length(y)){
    mu[j] <- mu1[ID[j]] + gamma1 * g[j] + gamma2 * l[j] +gamma3 * s[j] + gamma4 * t[j] +
gamma5 * v[j] + gamma6 * p[j] + gamma7 * z[j]
    y[j] ~ dnorm(mu[j], tau2)
  }
}
```