**Tag-recapture Antarctic toothfish random effects environment**

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**Abstract**

Words

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## 1 Introduction

Growth in fishes arises from complex behavioral trade-offs for each individual in a population. Growth (measured as an increase in standard length) arises from the allocation of energy between increased size (length) and increased condition (i.e., weight at length). Individuals can also increase their rate of energy acquisition via increased foraging activity, but increased foraging may also cause changes in the risk of predation. Finally, environmental conditions modulate the potential for growth, as well as the trade-offs faced by individual fish. For example, increases in water temperature are associated with increased activity levels but also increased energetic demands for maintaining existing body tissue, such that the net effect of changing temperature on growth may vary among individuals. Similarly, changes in survival rates (via fishery harvest) may favor earlier maturation, thus affecting the relative allocation of energy between growth and reproduction.

Many recent studies of captive or wild populations have demonstrated persistent differences in behavioral or phenotypic traits among individuals (termed differences in “personality”). Persistent differences in activity level or tolerance of predation risk (i.e., when foraging in high vs. low-quality habitat) will likely lead to persistent differences in growth rates. Variation in growth rates has been discussed for over 100 years for fish populations. For example, persistent differences in growth rate, combined with size-selective harvest, will result in older individuals being composed primarily of slow-growing individuals (termed “Rosa Lee’s Phenomenon”). Failure to account for persistent differences in growth rate can therefore lead to biased estimation of average growth rates in wild populations, and population dynamics models are increasingly developed to account for these effects (Taylor and Methot 2013).

In addition to persistent differences in growth rate among individuals, populations may experience synchronous variation in growth rates in a given year. For example, annual variation in water temperature may drive changes in metabolic costs as well as food availability in upwelling systems such as the California Current (Black et al. 2010), and this may cause all individuals to have elevated or depressed growth rates in a given year. Recent meta-analytic work has supported the hypothesis that time-variation in average growth rates is the rule rather than the exception for marine populations (Thorson and Minte-Vera In press). Similarly, many studies have illustrated persistent spatial differences in growth rates (Gertseva et al. 2010), e.g., where populations often have a smaller maximum size in warmer waters.

We therefore hypothesize that most marine populations will have multiple sources of variability in individual growth rates, including:

1. Persistent variation among individuals (i.e., some individuals grow faster or to a larger size than others)
2. Spatial variation (i.e., some areas have different size at age on average than others)
3. Temporal variation (i.e., all individuals having elevated or depressed growth rates in a given year)
4. Residual variation (i.e., individuals will have spurts and drops in growth rates).

Mixed-effects models are generally used to decompose variance in a data set into multiple sources of variability (Thorson and Minto In press). Mixed-effects models accomplish this by estimating true size at age as a latent variable, which is integrated across during estimation of growth parameters. Hierarchical models are increasingly advocated as a strategy to partition variability into multiple sources, and hence to interpret which source of variance is worth further study (Larsen et al. 2001, Gelman 2005).

Growth rates in natural populations are generally estimated using capture-mark-recapture (CMR) models. In CMR studies for marine fishes, thousands of individuals are typically captured and marked with a persistent and unique tag, and then measured and released. If a tagged individual is recaptured, it is often killed and its age at recapture identified via analysis of hard parts. Given the known time between capture and recapture, its size and age at both times can be calculated. This study design allows a model for growth increments to be fitted to size and age data for two times for each individual in a data set.

Many studies have examined the impact of persistent or residual variation on estimation of growth patterns using CMR data for wild marine populations (Sainsbury 1980, Francis 1988). However, few studies have explicitly modeled multiple sources of variability in growth rates. One exception is Shelton et al. (2013), which modeled persistent, temporal, and residual variation in growth rates in the analysis of data from a growth experiment for steelhead trout. In this study, we additionally incorporate sex-specific differences and spatial variation in growth rates, and implement the model using maximum marginal likelihood estimation. The code is distributed as a publicly available package in the R statistical environment, and is illustrated using CMR data for Antarctic toothfish (*Dissostichus mawsoni*). Using these data, we show that …. [1-2 sentence summary of most important result for toothfish].

**2 Methods**

We start with the specialized von Bertalanffy growth function:

(1)

where *dL/dt* is change in length as a function of time, *a* scales with energy acquisition, and *k* represents metabolic upkeep costs. Variation among individuals can be estimated by treating each individual's demographic parameters as a random effect that arises from a population-level distribution (Thorson and Minto In press). Here, we treat metabolic upkeep costs as varying among individuals, due to differences in ambient temperature, intrinsic variation in activity levels, and other factors:

where (2)

where *ki* is the upkeep costs for individual *i* and *μk*  is the average *k* among individuals in the population.

Individuals that are more highly active may obtain more food (increased *a*) and simultaneously have greater upkeep costs (increased *k*). Following Shelton et al. (2013), we include this association via the following equation:

(3)

where *Ψ* determines whether upkeep costs (*ki*) and energy acquisition rate (*ai*) are highly correlated (*Ψ=1*) or independent among individuals (*Ψ=0*), and *γ* controls the average energy acquisition rate among individuals.

We also assume that environmental conditions experienced by each individual will vary over time, such that each individual will also have variation over time in their upkeep costs (*ki*), in turn affecting their access to food (*ai*). In particular, we assume that upkeep costs for a given individual *i* for a short time interval *t* can be approximated by a constant value (*ki,t*), which will vary around the average value for this individual (*ki*). In the proceeding, we use a time interval of one week (7 days), while confirming that results are similar for other small time intervals. Integration then yields:

(4)

where

where *Δt* is the number of time-periods elapsed between length intervals and *nΔ* is the number of time-periods per year, such that *k* is the Brody growth coefficient (with units years-1). The average asymptotic length for individuals in the population can be found by setting Eqn. 1 equal to zero, substituting in Eqn. 2, and rearranging:

(5)

Readers are referred to Shelton et al. (2013) for an expanded model that also incorporates variability in *γ* over time.

## 2.1 Estimation

We implement this model using Template Model Builder (TMB;available from: <https://github.com/kaskr/adcomp>) software called from the R statistical environment (R Core Development Team 2013) and all code necessary for replicating the case study and simulation experiment are publicly available (<https://github.com/quantifish/TagGrowth>, Appendix A). Estimation was conducted using maximum marginal likelihood (Thorson and Minto In press), while marginalizing across the probability of all random variables representing variation among individuals and over time.

**2.2 Case study application**

Antarctic toothfish are large Nototheniids (growing more than 2 m in length, over 100 kg and living for up to 50 years of age) native to the Southern Ocean. The exploratory toothfish fishery in the Ross Sea region began in 1997 and is managed by The Commission for the Conservation of Antarctic Marine Living Resources (CCAMLR). Since then the fishery has increased to about 3000 t per annum. Fishing is restricted to the summer months, once the ice shelf recedes allowing vessels access to the region. The Antarctic toothfish tagging programme was initiated in the in the 2001 fishing season by New Zealand vessels involved in the fishery. In 2004, toothfish tagging was made compulsory for all vessels participating in the fishery. The tagging programme records information on the date, depth, location, sex, and size of each tagged/recaptured fish. A small subset of the recaptured fish are aged by reading their otolith.

We identified those fish that had been tagged, recaptured and aged upon recapture. This yielded 315 individuals of which 166 were female and 149 male. We fit several different versions of the model to these data, these included:

1. No random-effects
2. Random-effects for upkeep costs only (log(*ki*))
3. Time varying individual random-effects only (*zi,t*)
4. Time varying individual random-effects and random-effects for upkeep costs (log(*ki*) and *zi,t*)
5. Same as 4 above but include fishing year effect

The simulation study illustrated that the model had little ability to identify the value of *Ψ*. We therefore fixed the value of *Ψ*=0. We also fit a model where fishing year *y* (a fishing year was defined as …) is incorporated as a random-effect applied to the average energy acquisition rate parameter *γ*, thus we have:

where (6)

This requires the estimation of a deviation parameter from the fishing year that the first fish was born until the most recent fishing year that a fish was recaptured. The effect of seasonality on growth rates could not be included because of the timing of the fishery (i.e., fishing only occurs during the summer months).

## 2.1 Simulation

A simulation study was done to validate the model. Four different scenarios were simulated including: no random-effects, random-effects for the upkeep costs *k* only, time varying random-effects for *z* only, and random-effects for *k* and *z*. A power analysis was done for each of the four scenarios where 50, 100, 250 and 500 individuals were simulated. This yielded 16 different simulation experiments. We did 200 replicates for each of the scenario/power combinations.

The model parameters *t0*, *k*, *L∞* and the coefficient of variation of growth were taken from Dunn et al. (2006) and used to derive the values of several parameters in the simulation study. Where required parameters were converted to have weekly units (i.e. *k*, *t0*, age). The parameters *L0* and *γ* can be calculated as:

(7)

and

(8)

The parameters *L0*, *k* and *γ* were all set to be sex-specific (Table 1a). Initial exploration illustrated that the model had little ability to identify the value of *Ψ*. We therefore fixed the value of *Ψ*=0. The standard deviation parameters *σ*obs, *σk*, and *σz* were set at values that resulted in reasonable variation in individual length trajectories (Table 1b). The parameter *σk* was set to be sex-specific, *σ*obs and *σz* were not.

For each individual in each of the scenario/power simulations, sex was sampled with replacement from the observed sex structure in the toothfish data set. The age at release, age at recapture and time at liberty were sampled independently from the observed toothfish data set, then one of the three variables was chosen at random and calculated using the remaining two variables (e.g., if age at recapture was chosen at random it was calculated as the age at release plus the time at liberty) and rounded to the nearest integer.

The model was fit to the data for each of the 200 replicates in each of the 16 simulation experiments.

## 3 Results

## 3.1 Simulation

* Do table showing number of pdh fits for each of the 4 scenarios. Also show true par values, and mean/median of estimates. Discuss the numbers of pdh fits for each simulation experiment.
* Parameters muk, gamma and L0 well estimated in all cases, distribution of estimates gets tighter as the power is increased from 50 to 500. Figure X.

## 3.2 Case study application

* Need to actually fit all of these models again, this won’t take long though. The fishing year effect model also needs to be run. The old runs for this seem to have gone amiss, need to hunt down these files to check how to calculate fishing year.

## 4 Discussion

* Mention how when the model was fit to annual rather than daily growth increments that the estimated parameters resulted in biased high growth schedules.
* Growth shock or growth retardation due to tagging. Tag shock has been estimated before as about 0.7 year lost in growth. Confounded by live/dead.
* Snapper may also have some data like this.
* Seasonality

## 5 Conclusions

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Table 1a – Parameter values used for all scenarios in the simulation experiment.

|  |  |  |
| --- | --- | --- |
| **Parameter** | **Female** | **Male** |
| *L0* | -0.3409 | 3.9777 |
| *k* | 0.00173 | 0.00179 |
| *γ* | 0.3119 | 0.3024 |
| *Ψ* | 0.0 | 0.0 |

Table 1b – Parameter values that vary among scenarios in the simulation experiment.

|  |  |  |  |
| --- | --- | --- | --- |
| Scenario | Parameter | Female | Male |
| No variation | σobs | 0.102 | 0.102 |
|  | σk | - | - |
|  | σz | - | - |
| Variation in *k* | σobs | 0.05 | 0.05 |
| σk | 0.1 | 0.2 |
|  | σz | - | - |
| Variation in *z* | σobs | 0.05 | 0.05 |
| σk | - | - |
|  | σz | 0.3 | 0.3 |
| Variation in *k* and *z* | σobs | 0.05 | 0.05 |
| σk | 0.1 | 0.2 |
| σz | 0.3 | 0.3 |

Table 2 – List and definition of symbols used in the text and equations.

|  |  |  |
| --- | --- | --- |
| **Parameter name** | **Symbol** | **Units** |
| The number of time periods per year |  | - |
| The hypothetical length at time |  | cm |
| Anabolic rate |  |  |
| Energy expenditure rate (“Brody growth coefficient”) |  | years-1 |
| Anabolism coefficient |  |  |
| Allometric scaling of anabolism and energy expenditure |  |  |
| Time variation |  | cm |
| Asymptotic maximum length |  | cm |
| The hypothetical time at which |  | years |
| Observation error standard deviation |  | - |
| Catabolic rate variance |  | - |
| Annual deviation variance |  | - |
| Time variation variance |  | - |
| **Data** | **Symbol** | **Units** |
| Time interval |  | weeks |
| Length at time *t* |  | cm |
| Year at time *t* |  | years |
| **Indices** | **Symbol** | **Units** |
| Individual |  | - |
| Time |  | weeks |
| Sex |  | - |
| Year |  | years |

Table 2 – List of simulation results.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Random effects | pdH | L0 | k | gamma | Sd obs |  |  |  |
|  |  |  |  |  |  |  |  |  |
| None |  |  |  |  |  |  |  |  |
| k |  |  |  |  |  |  |  |  |
| z |  |  |  |  |  |  |  |  |
| k and z |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |

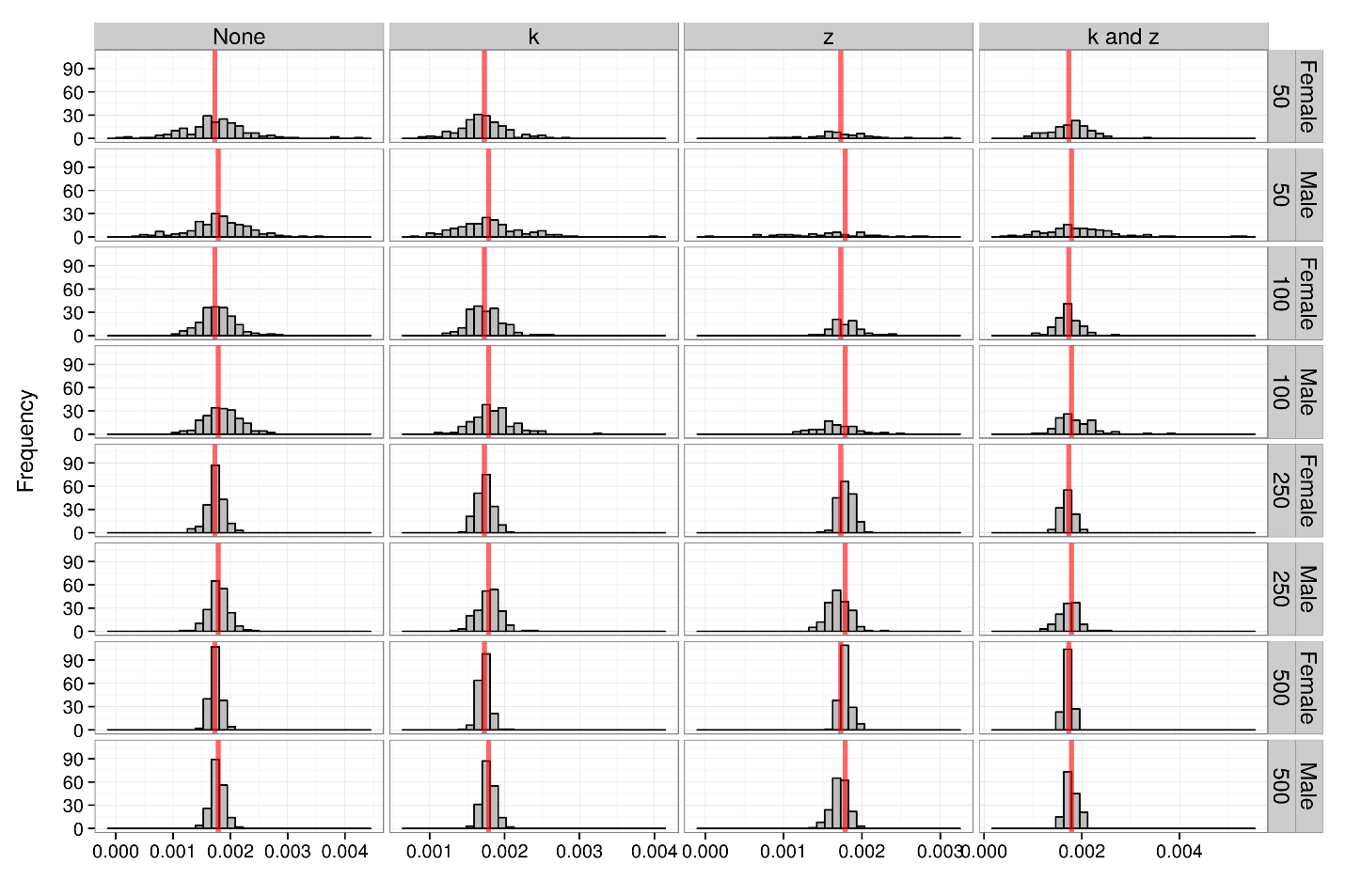


Figure X – Estimated value of muk in each of the simulation study experiments.

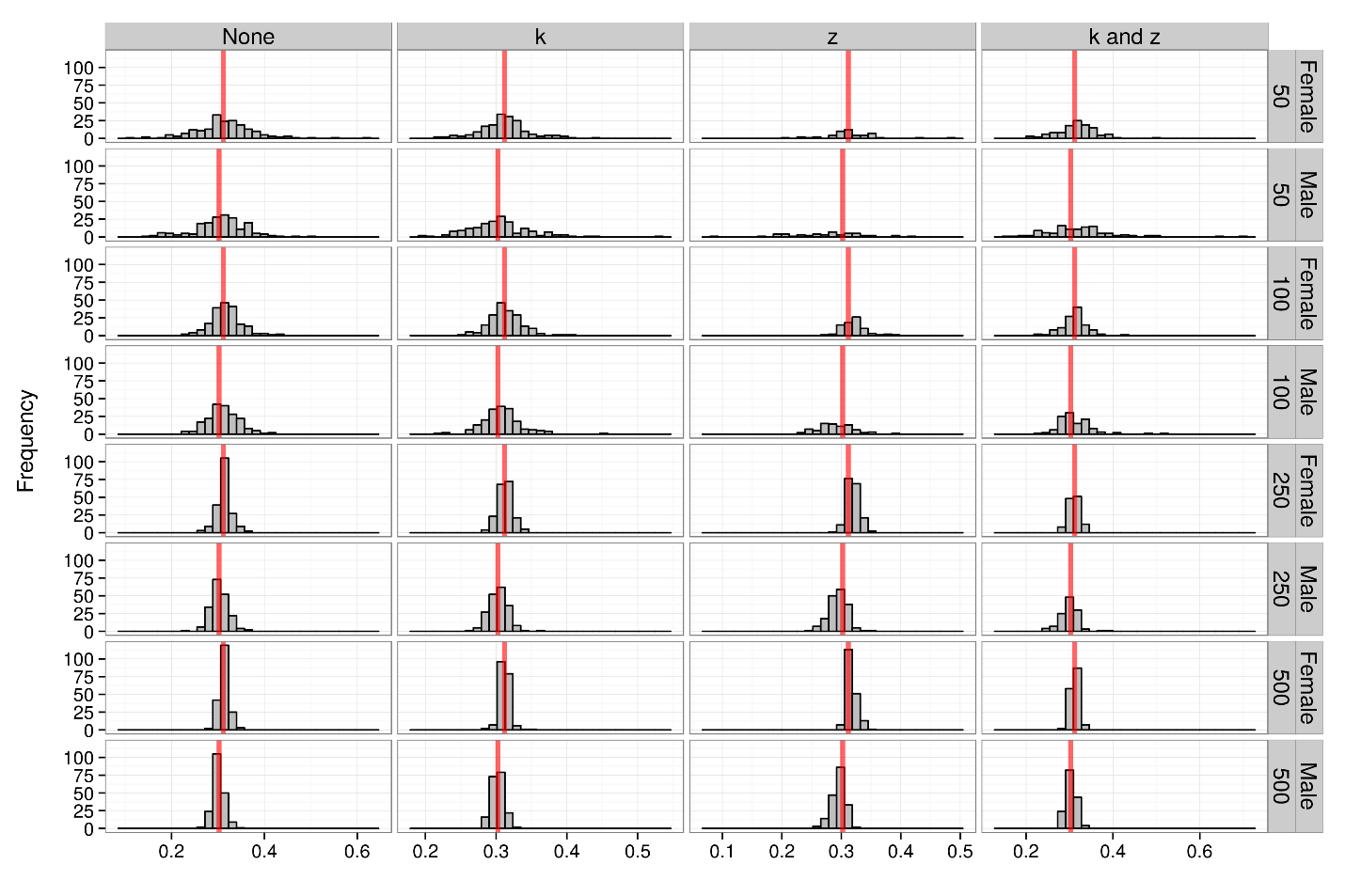


Figure X – gamma sims

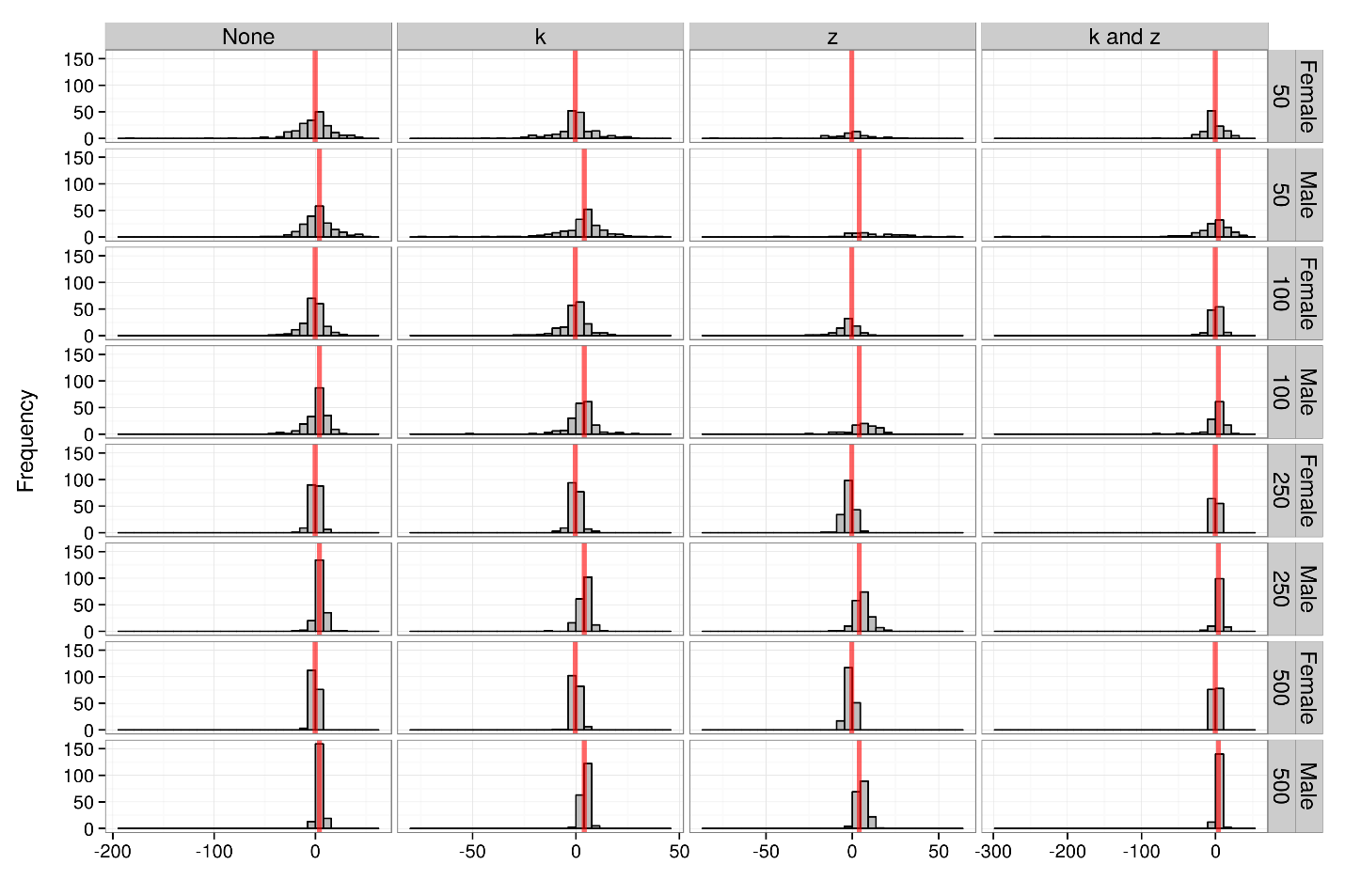


Figure X – L0 sims

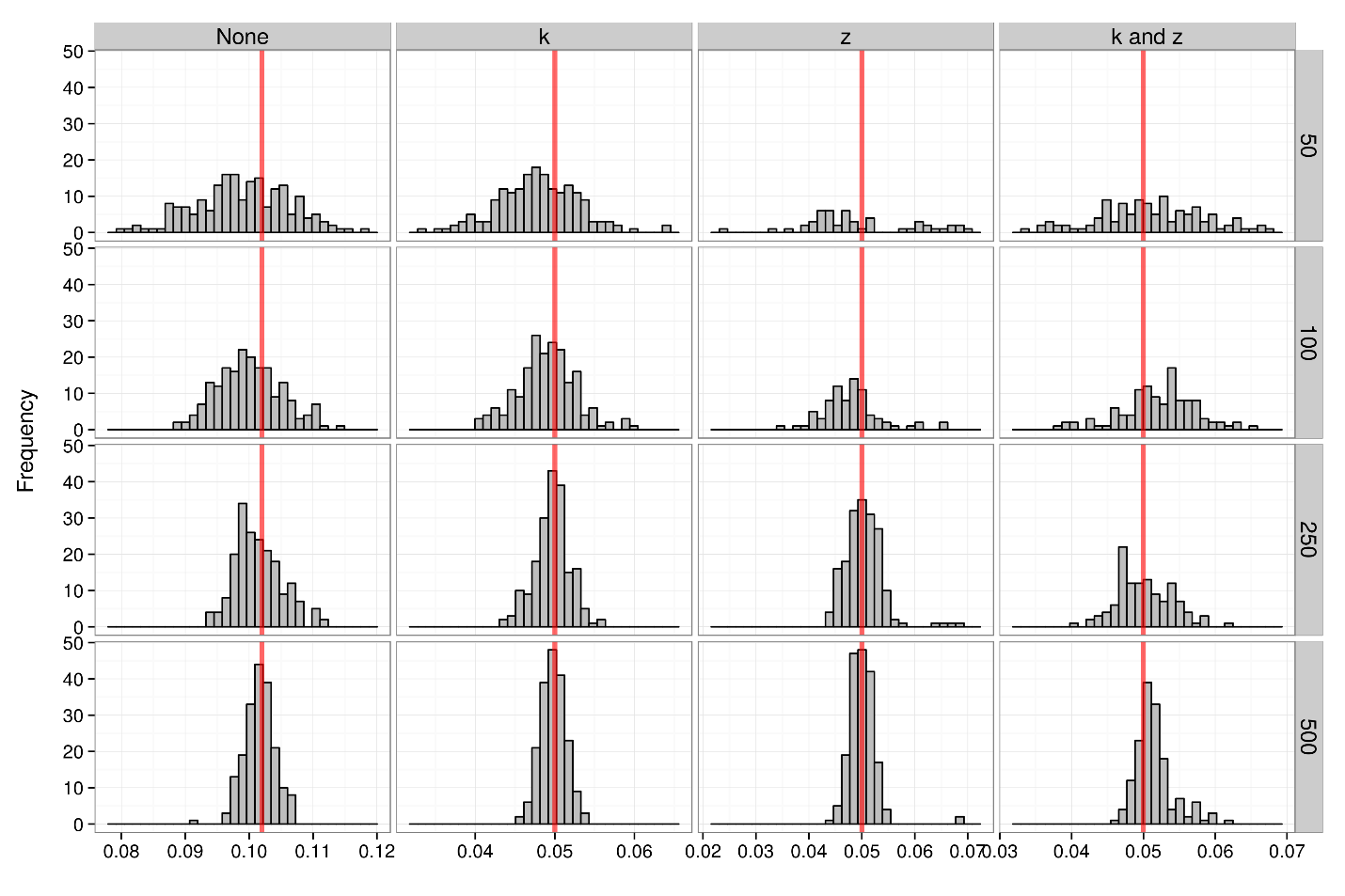


Figure X – sdobs sims, could half the height of this fig

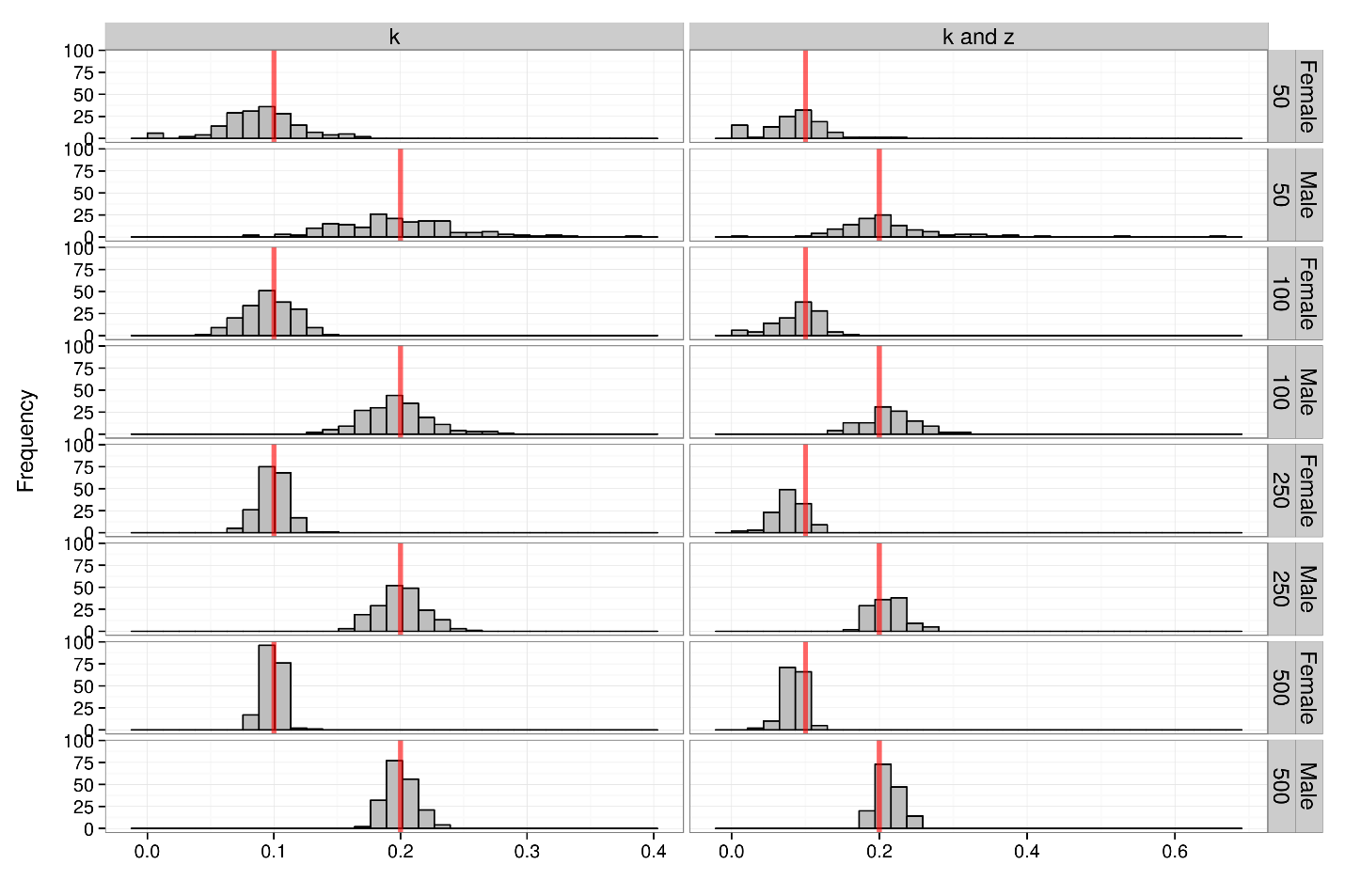


Figure X – kdev sims, could half the width of this fig

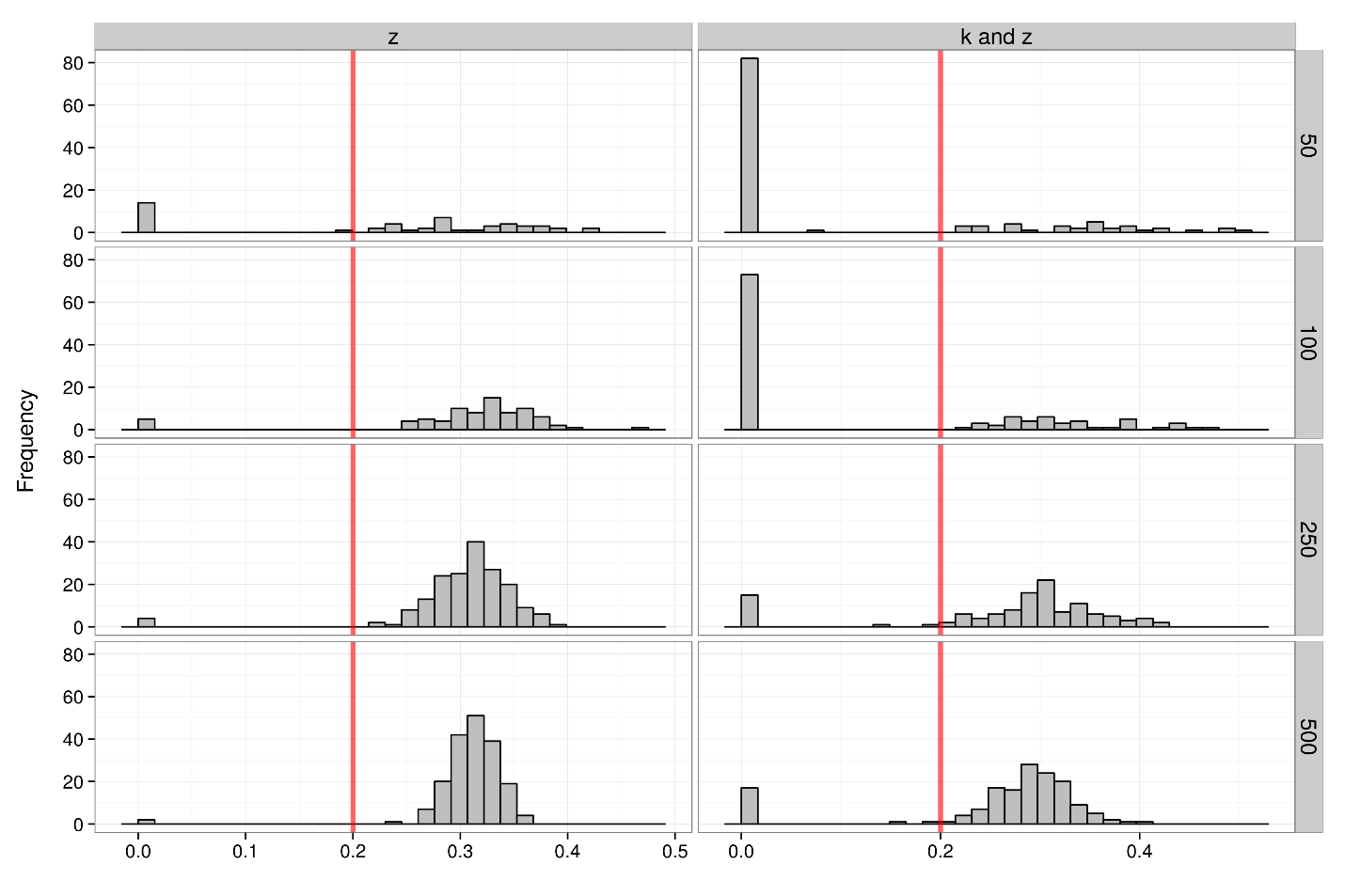


Figure X – sdz sims, could half the height and width of this fig. This will look different once the simulations that I f’ed up and am currently running are done.

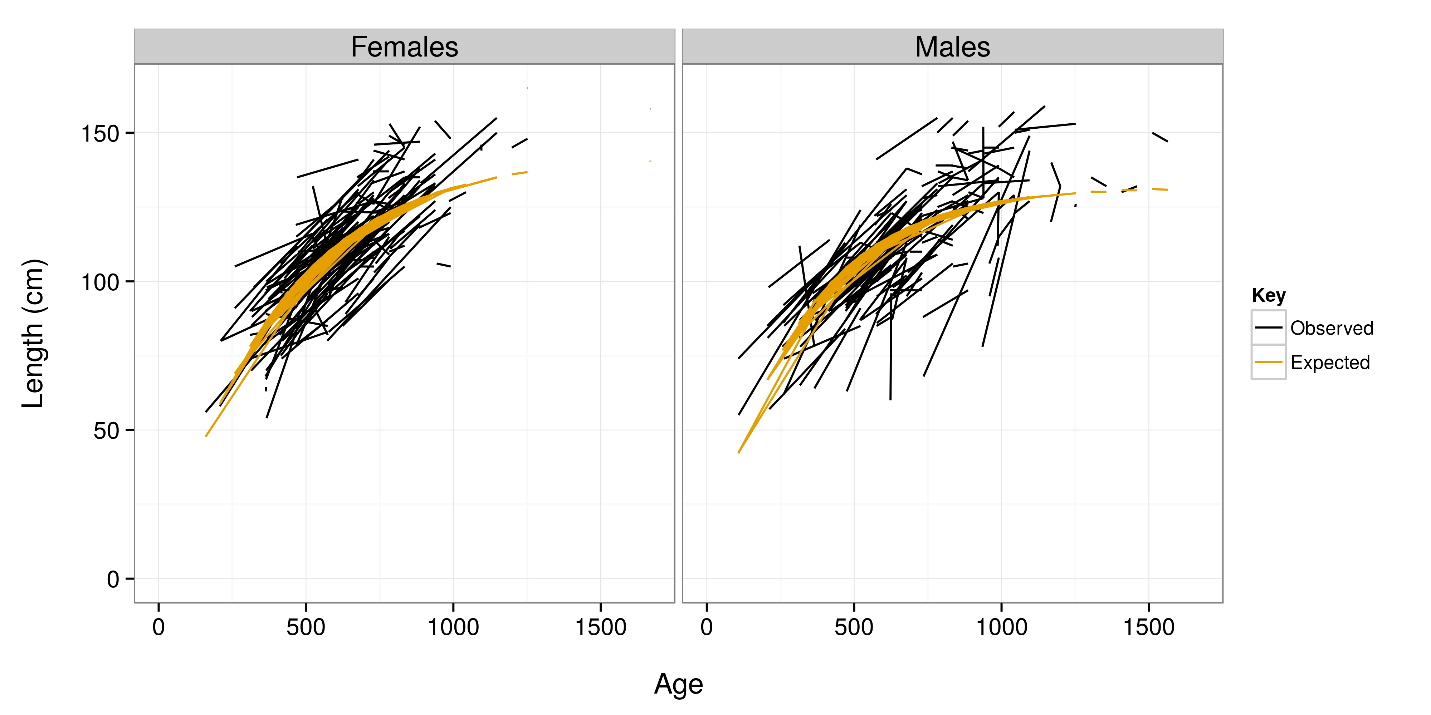


Figure X – no random effects

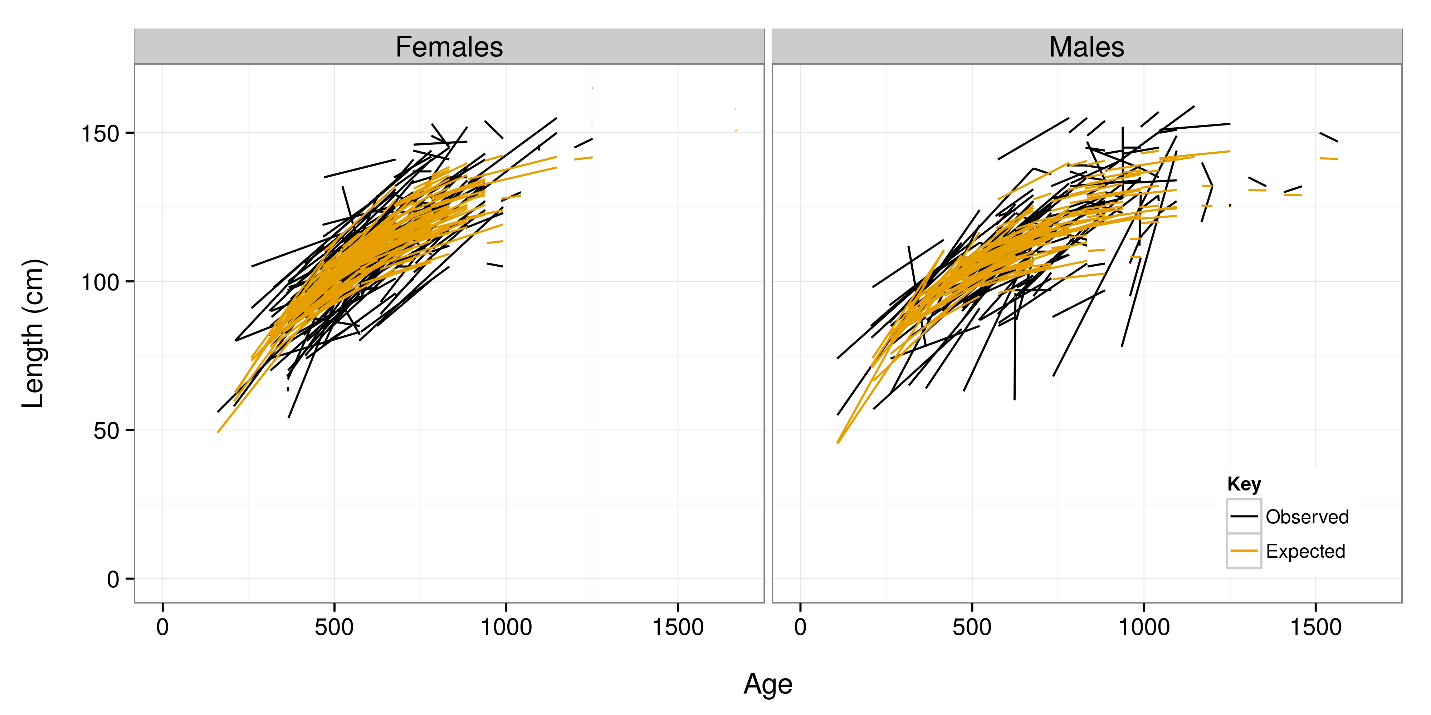


Figure X – random effects of k

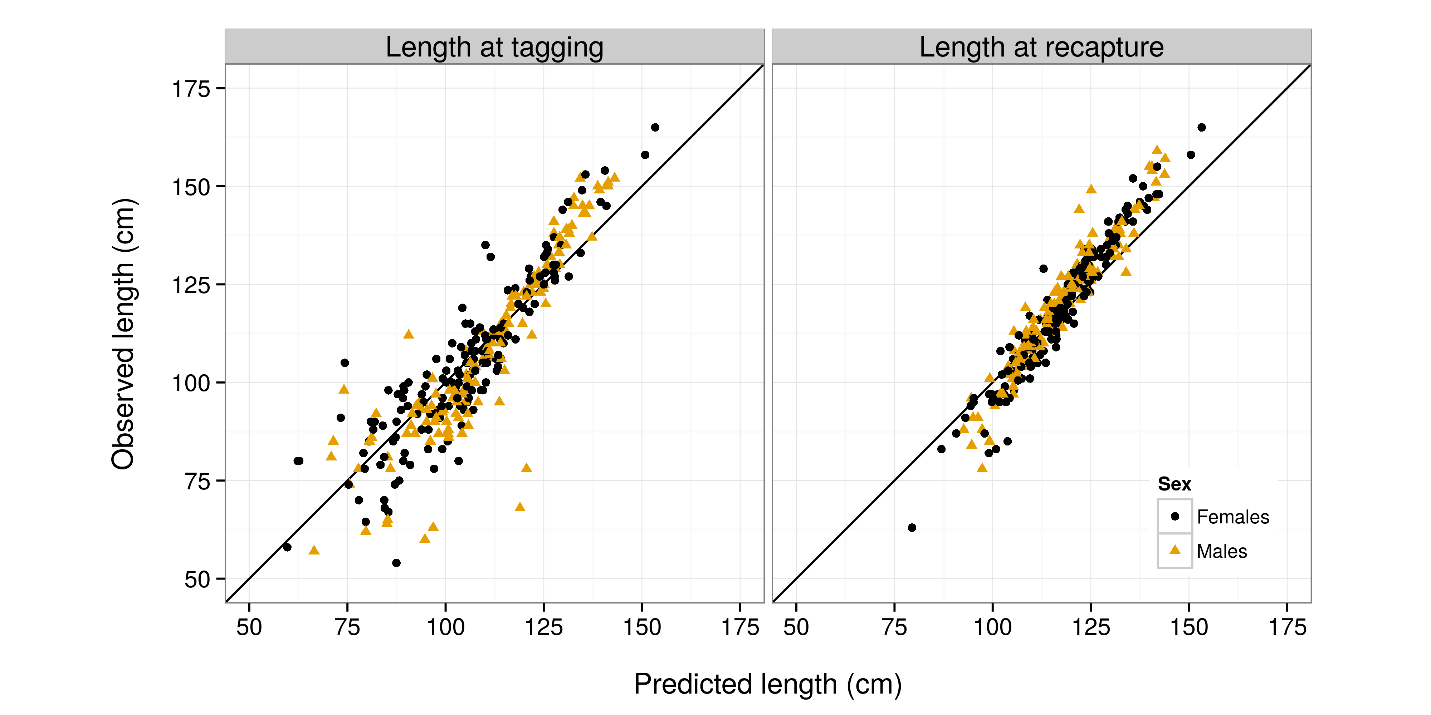


Figure X

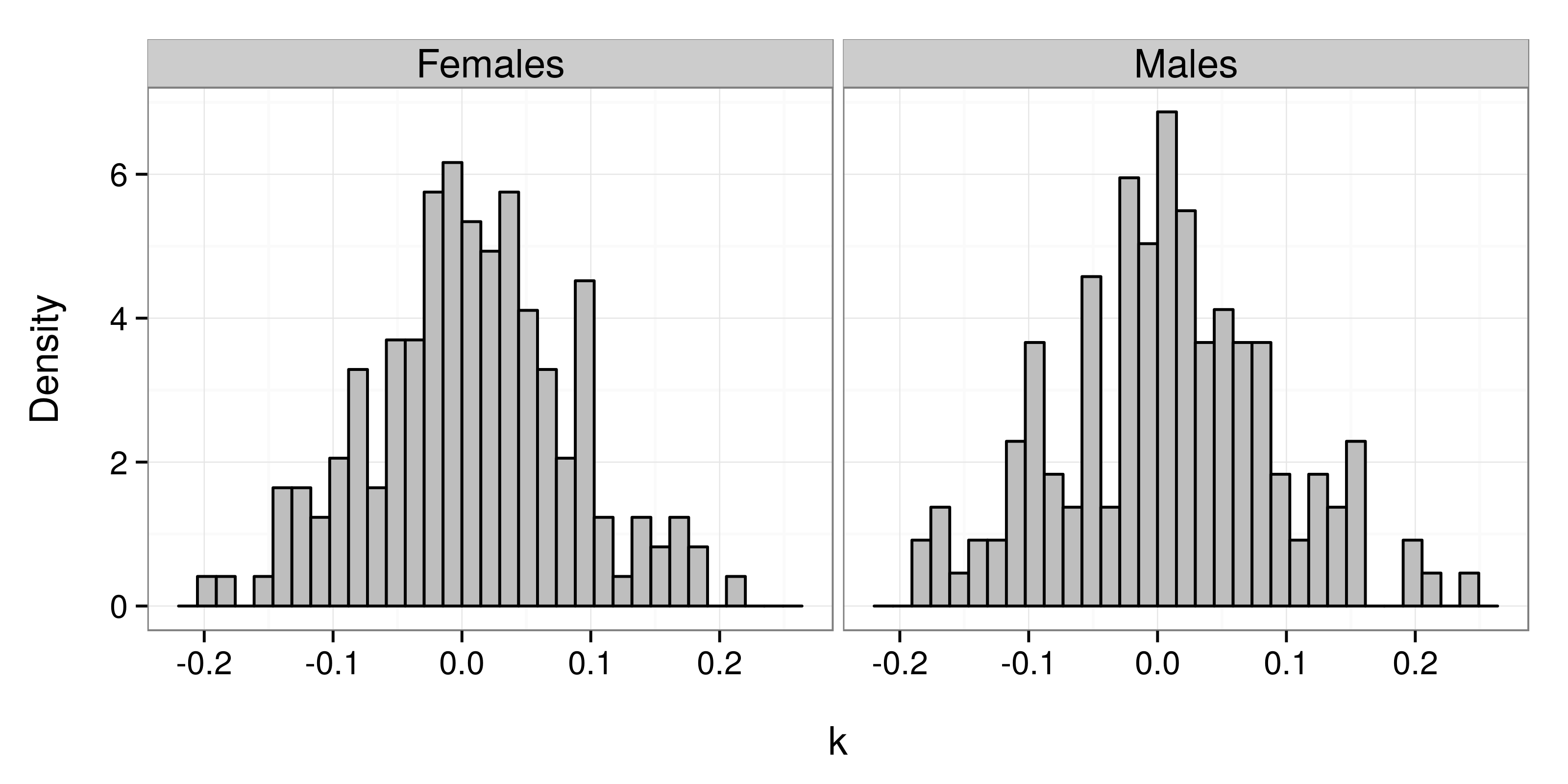


Figure X