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A new statistical modelling framework to interpret ivory seizures data

A Technical Report describing the new modelling framework for analysing seizures data from the Elephant Trade Information System

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Enhancing the Elephant Trade Information System to Guide CITES Policy

1. Introduction

This report describes the statistical modelling framework developed under Darwin Initiative Project 17-020 “Enhancing the Elephant Trade Information System to Guide CITES Policy”. The aim of the statistical modelling is to use records of illegal ivory seizures in the Elephant Trade information System (ETIS) to produce quantitative summaries of levels and trends in the illegal ivory trade for reporting to the Convention for International Trade in Endangered Species of Wild Fauna and Flora (CITES).

In this report we describe the underlying concepts underpinning the modelling framework (Section 2), the characteristics of the data (Section 3) and the models we have developed (Section 4). Although the statistical modelling is complex our aim is to produce simple indicators of the trade for reporting. Here we present the Transactions Index (TI) and Weights Index (WI) that describe the number and total weight of illegal ivory transactions. These and other derived variables (Section 5) were used to present results to CITES 16th Conference of the Parties (Milliken et al 2012) and in a rapid response assessment of the African Elephant crisis (UNEP et al 2013)

1.1 Conceptual Framework

The statistical challenge with illegal ivory seizures data is that countries differ in their ability to make and report seizures and these differences are not directly measurable. Hence simple summaries of illegal ivory seizures data will be biased. For example two countries may report the same number of illegal ivory seizures to ETIS in any one year suggesting that they have similar levels of illegal ivory activity in their country. In fact country A may have very good law enforcement and so seize a large proportion of illegal ivory shipments that pass through the country. In addition, this country may also have the resources to ensure that all such seizures are reported to ETIS. In comparison, country B may have very poor law enforcement so that only a very small proportion of illegal ivory shipments that pass through the country are seized. Furthermore the person responsible for reporting these seizures to ETIS may have so many other commitments that they do not report many of these seizures to ETIS. Thus, there is much more illegal ivory trade activity in country B than in country A but a simple summary of the number of reported seizures by each country does not demonstrate this.

Our modelling framework identifies proxy variables that account for some of the differences in reporting and seizure rates between countries and over time. From this we calculate bias-adjusted and smoothed estimates of illegal ivory trade activity. We describe methods generically but when necessary illustrate with the decisions made for the analysis presented to CoP16 [1] describing trends in the illegal ivory trade from 1996 to 2011.

2. Data

The main component of ETIS is the database of illegal ivory seizure records reported by CITES Management Authorities or other organisations. ETIS also holds subsidiary data thought likely to be useful for modelling or analysis purposes. The subsidiary variables are mainly indicators of governance, economic and social development and law enforcement, mostly obtained from secondary sources.

2.1 Reported Seizures Data

ETIS contains an ever increasing number of records of reported ivory seizures, starting from 1989. To include a seizure in the analysis presented here data on the following items must be recorded: the year in which the seizure was made; the country that made the seizure; the quantity of raw ivory (tusks or part tusks) in kilogrammes or number of pieces; the quantity of worked ivory (carved or semi-carved pieces) in kilogramme or number of pieces. The weights of seizures can vary greatly in size from, for example, the lock of a necklace weighing 0.56g to a shipment containing several tonnes of raw ivory. We would not expect the countries through which these two very different shipments pass to be the same and the changes in trade routes over time may also differ. Hence we want to ensure that our modelling captures the differences between large and small seizures and those of raw and of worked ivory.

About half of the ETIS records report the weight of the ivory. To be able to compare weights of worked and raw ivory seizures all worked ivory weights are divided by 0.7 to account for an average 30% wastage of ivory in the carving process (Milliken, 1989). The remaining records record the number of pieces of ivory, but not the ivory weight. The weights for these data were estimated from the number of pieces using a model described in the Methods section. The precision of the estimated weights is low because of data variability. Furthermore the recorded weights for many of the large seizures are only rough estimates – for example “four tonnes” – because the authorities may not have the means to weigh the consignment. Hence in our analysis we used weight classes rather than weights and our weights model was used to assign seizures to broad weight categories. These categories, representing raw and worked ivory separately, are: less than 10kg (small), 10kg to less than 100kg (medium), and 100kg or more (large).

2.2 Data Selection

In addition to reporting the country in which the seizure was made, many records also report the countries through which the shipment passed or was destined for, thus implicating other countries in the reported seizures. Some countries contributed little to the overall trade because they made or were implicated in very few seizures in total, for example only one or two seizures in 16 years, or seizures totalling only a small weight. Other countries may have reported very few seizures themselves but been implicated in many seizures made by other countries suggesting that these countries potentially play a major role in the trade.

The purpose of our analysis is to identify trends and countries that play a major role in the trade, and a principal objective of the bias adjustment is to correct for countries that report few seizures themselves but are heavily involved in the trade. We therefore chose to select all countries that met at least one of two criteria which we illustrate with the 16 years of data from 1996 to 2011: (1) they had made or were implicated in at least 30 seizures in total over the 16 years; (2) they had made or were implicated in seizures with total weight of at least 300kg, over the 16 year period (using the estimated weight in cases where no ivory weight was provided).

The resulting dataset for analysis consists of the number of raw and worked seizures in each weight class that were seized by each country in each year. Seizures that contained both raw and worked ivory were included in the appropriate raw and worked ivory weight classes. The selection criteria mean that some countries in the dataset may have themselves reported zero seizures over the relevant time frame.

2.3 Variables affecting the seizure rate

Seizure rate was assumed to be a function of law enforcement (LE) *effort* and LE *effectiveness*. In principle, law enforcement effort could be measured by data on budgets, personnel, training, equipment, etc. Such information is impossible to obtain consistently across many countries. We therefore develop an indirect measure of LE effort using past ivory seizure records in ETIS. As a proxy for LE effort, we define the *LE ratio* for a country in a given year as the proportion of all seizures that the country was involved in that were made by the country themselves in that year. Small values suggest that a country has poor LE effort as they make very few seizures themselves, whereas high values (close to one) suggest that a country is seizing a large proportion of what passes through their country in a specific year. The proxy variable that we used in the analysis was *LE1*, the one-year lagged LE ratio, to represent the situation where last year's LE ratio represents the law enforcement environment for the current year.

Effectiveness of LE was thought to vary according to the background level of corruption or governance, and also the general level of socio-economic development in the country. Several measures of corruption, governance and socio-economic development are available on a country by year basis in the public domain. These include:

- *CPI: Corruption Perceptions Index* (Transparency International);
- six World Bank's *World Governance Indicators* (Kaufmann et al. 2010)
  - *Voice and Accountability*,
  - *Political Stability*,
  - *Government Effectiveness*,
  - *Regulatory Quality*,
  - *Rule of Law*
  - *Control of Corruption*;
- *HDI: Human Development Index* (UNDP, 2011)
- *GDP*: per capita GDP (World Economic Outlook Database, International Monetary Fund);
- *Gini coefficient*, a measure of income inequality (World Bank Poverty Indicators).

Some variables were not available for all countries in all years, and missing values were estimated by interpolation. For *Gini Coefficient* and *HDI*, it was not possible to obtain time-varying values of two of the variables representing development, specifically so the means of available values for each country were used instead.

The strength of wildlife trade legislation in a country was also thought to potentially be a contributory factor. An indicator of the strength of wildlife trade legislation (*leg*) was available from the CITES Secretariat. This was a simple score on a 1/2/3 scale arising from the CITES National Legislation Project – an on-going initiative that monitors the extent to which the country meets CITES requirements for legislation (Milliken et al, 2002).

2.4 Variables affecting the reporting rate

Reporting rates could potentially vary according to both the readiness of the country to submit data, and the effort made by the ETIS database manager to obtain it. No direct measures of the former were available, so again proxy variables for it were sought. The key variable used was the *CITES reporting score*, an indicator based on each country's experience in fulfilling reporting requirements to the CITES Secretariat. The variable was calculated as the number of CITES Annual Reports submitted as a proportion of the number of years the country had been a CITES Party. The idea is that this proportion could be taken as an indicator of the seriousness with which the country meets its obligations under CITES (including reporting to ETIS). The data required for this ratio were provided by the CITES Secretariat (Geneva).

The effort made by the database manager to collect seizures data varied according to the way that each seizure was reported to ETIS. Technically speaking, a seizure should be reported by the CITES Management Authority (CMA) to ETIS within 90 days of the seizure being made, according to the recommendation in CITES Resolution Conf. 10.10. In practice, however, seizures enter the database in different ways. In the past, certain countries have been subjected to *targeted* data collection in which an ETIS representative visits the country, reviews law enforcement records and collects information on elephant product seizure cases. Although little targeting has occurred in recent years, countries are often *prompted* by mail, e-mail or CITES notifications to submit seizure records. Other records arrive unprompted, some originating from sources other than the CMAs themselves, such as NGOs or other unofficial sources. Some CMAs report sending records that have been collected in the context of national automated systems holding wildlife trade seizure information. In these cases, we might expect that most, if not all, seizures made in that country are reported. In the case of passive, unsolicited reporting it is less clear that all seizures are reported to ETIS. To capture this variability each record in ETIS is scored according to whether it was obtained from targeting or prompting, or from an automated mechanism, or whether it was received passively. We define the *data collection score (DC)* for a country as the proportion of records in a year that came from a targeted/automated/prompted mechanism.

3. Methods

Weight classes were estimated for seizure records that only record the number of pieces of ivory, rather than the weight of ivory. Then a model is fitted to estimate the number of transactions by ivory class, country and year; from this the Transactions Index could be obtained. Third, a model of the weight per seizure was required for both worked and raw ivory. Combining this with Transactions Index the Weights Index was obtained.

3.1 Estimating weights of seizures from the number of pieces in the seizure

Of all ivory seizures in the database, about 53% have number of pieces but no weight recorded. In order to allocate seizures to weight classes, the unknown weights were estimated from the number of pieces. This was accomplished by fitting a regression model, described here, separately for raw and worked ivory seizures, of weight on number of pieces based on all cases where both number of pieces and weights are known. All available data for all available years since1989 were used for this modelling.

Exploratory data analysis suggested that (1) models with weight and number of pieces both on a log scale should be tried initially, and (2) the relationship between number of pieces and weights was time-dependent. The linear predictor was therefore chosen to contain orthogonal polynomial functions of ln*(#pieces)* and of *year* of seizure. Frequentist regression methods were used for this modelling exercise. Trial modelling with *weight*, and subsequently ln*(weight)*, as response variable resulted in highly residuals that were both heteroscedastic and highly skew, so a power transformation of the response was sought using the Box-Cox method (34). For this purpose, a linear predictor with high-order polynomials (9 for each variable) was used to get the profile likelihood of the transforming power α. Having estimated α in this way (separately for raw and worked ivory), models with orthogonal polynomials of appropriate order were fitted using the transformed response variable $y = (weight)^{\alpha}$. The fitted model was

$$w_i^{\alpha} = \mu + \sum_{j=1}^{p} \beta_j \xi_j(x_i) + \sum_{k=1}^{q} \gamma_k \xi_k(t_i) + \varepsilon_i \,,$$

where, for the i^{th} seizure, x_i is ln*(#pieces)* and t_i is the year of seizure, $\{\xi(\ )\}$ are orthogonal polynomials and $\varepsilon_i \sim_{IID} N(0,\sigma^2)$.

This model was used to predict weights for seizure records where number of pieces was known but weight was not. It should be stressed that although there was some uncertainty in estimating weights in this way, notably for worked ivory, the only way that the estimated weights contributed to the final analysis was in allocating seizures with unknown weights to very broad weight classes, so the uncertainty was thought unlikely to have a major impact on the final modelling.

3.2 Statistical model for seizures data

We let y_{ikt} represent the number of reported seizures in country $i = 1,\ldots,68$, ivory class $k = 1,\ldots,6$ and year $t = 1996,\ldots,2011$. Typically one would start modelling count data like this using a Poisson distribution, but initial exploratory models indicated severe over-dispersion and a negative binomial distribution (*34*) was therefore used instead. The statistical model is described as follows:

$$y_{ikt} \sim \text{NegBin}(p_{ikt}, r_k), \text{ where } 0 < p_{ikt} < 1 \text{ and } r_k \in \mathbb{Z}^+,$$

so that $$\Pr(y_{ikt} | p_{ikt}, r_k) = \frac{(y_{ikt} + r_k - 1)!}{y_{ikt}!(r_k - 1)!} p_{ikt}^{r_k} (1 - p_{ikt})^{y_{ikt}}, \text{ for } y_{ikt} = 0,1,2,\ldots$$

Smaller values of r_k indicate a greater degree of over-dispersion. Note that the model allows a different value of this parameter for each ivory class, but assumes it to be otherwise constant across countries and years.

In terms of this parameterisation, the mean value of y_{ikt} is

$$\mathrm{E}(y_{ikt}) \equiv \mu_{ikt} = \frac{r_k(1-p_{ikt})}{p_{ikt}}$$

A key assumption in the model was the factorisation of the mean $\mu_{ikt} = \lambda_{ikt}\phi_{it}\theta_{it}$, where $\lambda_{ikt} \geq 0$ is a measure of the expected number of unobserved class *k* ivory transactions in country *i* and year *t*. ϕ_{it} is the seizure rate and θ_{it} the reporting rate $(0 \leq \phi_{it}, \theta_{it} \leq 1)$ for country *i* in year *t*, both assumed constant across ivory classes.

The data were actually modelled as a multivariate process $\boldsymbol{y}_{it} = (y_{i1t}, \ldots, y_{i6t})$, with six dimensions representing the ivory classes, so we can write $\boldsymbol{\mu}_{it} = \boldsymbol{\lambda}_{it}\phi_{it}\theta_{it}$. Variation in $\boldsymbol{\lambda}_{it}$ over years was accounted for by fitting a polynomial function of *t*:

$$\log(\boldsymbol{\lambda}_{it}) = \boldsymbol{\alpha}_{0i} + \boldsymbol{\alpha}_{1i}\xi_1(t) + \sum_{j=2}^{p}\boldsymbol{\alpha}_j\xi_j(t)$$

where $\{\xi_j(t)\}$ are orthogonal polynomials of *t*. The random intercepts $\boldsymbol{\alpha}_{0i}$ and first order coefficients $\boldsymbol{\alpha}_{1i}$ were assumed to follow multivariate normal distributions: $\boldsymbol{\alpha}_{0i} \sim \mathrm{MVN}(\boldsymbol{\mu}_0, \boldsymbol{\Omega}_0)$ and $\boldsymbol{\alpha}_{1i} \sim \mathrm{MVN}(\boldsymbol{\mu}_1, \boldsymbol{\Omega}_1)$, with covariance matrices $\boldsymbol{\Omega}_0$ and $\boldsymbol{\Omega}_1$, respectively, thus accounting for correlated trends between the 6 ivory classes. With model parsimony in mind, the higher order coefficients $\boldsymbol{\alpha}_j$ were assumed constant over countries.

The country by year specific seizure and reporting rates are latent variables, but were modelled as functions of the candidate proxy variables described above as covariates (predictors). Given that they are proportions, the *logit* link function, $\mathrm{logit}(\pi) = \ln[\pi/(1-\pi)]$, was used to relate them to their linear predictors, so that $\mathrm{logit}(\phi_{it}) = \sum_m \beta_m x_{mit}$ and $\mathrm{logit}(\theta_{it}) = \sum_n \gamma_n z_{nit}$, where x_{mit} and z_{nit} are standardised values of the covariates. To avoid problems of parameter identifiability, the linear predictors for seizure and reporting rates had no intercept terms. A consequence of this is that, since the predictors were standardized, the seizure and reporting rates were each logit(0), or 0.5, when the predictors were at their mean values.

The model was fitted in a Bayesian framework and non-informative priors for all parameters were adopted throughout. Specifically, the priors for the model parameters were as follows:

$$\boldsymbol{\mu}_0 \sim \mathrm{MVN}\left(\mathbf{0}, \sigma^2 \boldsymbol{I}\right) \text{ and } \boldsymbol{\mu}_1 \sim \mathrm{MVN}\left(\mathbf{0}, \sigma^2 \boldsymbol{I}\right), \text{ where } \sigma^2 = 10^4$$

$\boldsymbol{\Omega}_0^{-1} \sim \mathrm{Wishart}\left(\boldsymbol{R}_0, 6\right)$ and $\boldsymbol{\Omega}_1^{-1} \sim \mathrm{Wishart}\left(\boldsymbol{R}_1, 6\right)$, where the scale matrices $\boldsymbol{R}_0$ and $\boldsymbol{R}_1$ were chosen roughly to reflect the covariances between ivory classes apparent in the data (*20*):

$\boldsymbol{R}_0 = \mathrm{diag}\left(50, 50, 5, 300, 75, 25\right)$ and $\boldsymbol{R}_1 = \mathrm{diag}\left(15, 10, 5, 150, 50, 10\right)$.

The coefficients α_{jk}, β_m and γ_n were all assigned non-informative $\mathrm{N}\left(0, 10^4\right)$ normal priors. An appropriate non-informative prior for the r_k parameter of the negative binomial distribution was a uniform distribution for r_k on a log-scale: $\ln\left(r_k\right) \sim \mathrm{Unif}\left(0, 10\right)$ (*20*).

The model was fitted by MCMC (Gelman et al, 2004) using the OpenBUGS software (Lunn et al, 2009) and the *R* system (R Core Team, 2012). The modelling strategy was first to estimate the polynomial trend in λ_{it}, then determine the best fitting combinations of covariates for seizure and reporting rates, described above, followed by re-checking the polynomial terms and re-fitting the covariates, proceeding iteratively until a stable model emerged. A polynomial of order $p = 6$ was found to fit well. Model fit was assessed using the DIC statistic (Lunn et al 2013, Spiegelhalter et al 2002). Further checking of the final model was achieved by plotting credible intervals of the posterior predictive distribution of the model mean and overlaying the data points (Gelman et al 2004).

The key outputs from the model are the λ_{it} parameter estimates. Their posterior means were interpreted as smoothed and bias-adjusted estimates of the illegal activity in ivory trade – *smoothed* because they are the estimated mean values of a stochastic process, and *bias-adjusted* because the estimated effects of imperfect seizure and reporting rates have been factored out. The transactions index, *TI*, was calculated as aggregated values of the λ_{it} parameter estimates.

3.3 Summaries of the Transactions Index

To estimate *TI* (with credible intervals to assess the uncertainty), simulations were taken from the posterior distribution of λ_{it}. These were derived by first simulating from the posterior distributions of the parameters $\alpha_{0ki}, \alpha_{1ki}, \alpha_{2k}, \ldots, \alpha_{6k}$ for each country *i*, each year *t* and each ivory class *k*, and then setting $\log\left(\lambda_{ikt}^{(s)}\right) = \alpha_{0ki}^{(s)} + \alpha_{1ki}^{(s)}\xi_1(t) + \sum_{j=2}^{6}\alpha_{jk}^{(s)}\xi_m(t)$,where the superscript *s* = 1, …, 5000 denotes the s^{th} simulation. By summing over all 68 countries we obtain the s^{th} simulation of *TI* for the ivory class *k* and year *t*: $TI_{kt}^{(s)} = \lambda_{.kt}^{(s)} = \sum_{i=1}^{68}\lambda_{ikt}^{(s)}$. The simulated distribution provides summary statistics and credible intervals from which estimates of the trend were obtained.

3.4 Estimating the Weight Index, WI

To derive the weights index, *WI*, the $\lambda_{ikt}^{(s)}$ estimates, rounded to integer values, were interpreted as estimates of the number of illegal ivory transactions by country, by year and by ivory class. For each simulated transaction, a weight was simulated from the estimated distribution of ivory weight per seizure, and then aggregated.

Fitting a distribution for the weight per seizure was a separate modelling exercise. The model was a Bayesian regression fitted to seizures with known weights (i.e. *not* using the records where weights were estimated from number of pieces – see section 4.1). The data chosen for this comprised all seizures records with known weights, including those, described in Section 3.2, excluded from the main modelling exercise. The distribution of weight per seizure was estimated separately for raw and worked ivory. The weight per seizure was allowed to change over time – a linear trend was found to be adequate to describe this change. A lognormal distribution with linear trend in the mean was found to fit poorly in the extreme values, but a robust regression of log(weight) based on the t-distribution did much better:

$\ln\left(w_{ik^*t}\right) = \delta_{k^*0} + \delta_{k^*1}t + \sigma_{k^*}\varepsilon_{ik^*t}$ where $\varepsilon_{ik^*t} \sim \mathrm{t}_{\nu_{k^*}}$ and w_{ik^*t} is the weight of ivory in the i^{th} seizure made in year *t*, and k^* = 1 for raw, or 2 for worked ivory. t_ν denotes the Student t-distribution on ν degrees of freedom. The use of Bayesian modelling here facilitated the estimation of ν from the data.

Non-informative priors for $\delta_{k^*0}, \delta_{k^*1}$ and σ^2 were used: $\delta_{k^*0}, \delta_{k^*1} \sim \mathrm{N}(0,10^4)$, $\sigma^{-2} \sim \Gamma(0.001, 0.001)$.

The prior for the degrees of freedom was uniform $\nu \sim \mathrm{Unif}(1,30)$, which allows fractional values.

After convergence, 5,000 iterations were drawn from the posterior distributions of the parameters and the predicted weights $w_{jk^*t}^{(s)}$ (s = 1, …, 5000) computed from the parameter values:

$\log(w_{jk^*t}^{(s)}) = \delta_{0k^*}^{(s)} + \delta_{1k^*}^{(s)} t + \sigma^{(s)} \varepsilon_{jk^*t}^{(s)}, \quad \varepsilon_{jk^*t}^{(s)} \sim \mathrm{t}_{\nu_{k^*}^{(s)}}$. The posterior distribution of the global weights index was calculated by summing over the weight for each ivory class. The total weight for ivory class *k* in year *t* is the sum of the first $\left[\lambda_{.kt}^{(s)}\right]$ simulated weights $w_{jk^*t}^{(s)}$ (where the brackets [*x*] indicate the nearest integer value of *x*) that fall within the correct ivory class. Since simulated values from the log-t distribution can be unreasonably large (although with low probability), simulations in excess of 8,000kg were rejected; this was considered a reasonable threshold as no seizures of this size have ever been observed. If A represents the set of weights meeting this criterion then:

$$WI_{.t}^{(s)} = \sum_{k=1}^{6} \sum_{A} w_{jk^*t}^{(s)} I_{[w_{k-1}, w_k)}(w_{jk^*t}^{(s)}) \text{ , where } A = \left\{ j : \sum_{j} I_{[w_{k-1}, w_k)}\left(w_{jk^*t}^{(s)}\right) \le \left[\lambda_{.kt}^{(s)}\right] \right\}$$

These are the *WI* values that were used to plot trends in the weights index and its credible intervals.

4. Use of outputs for CITES reporting

The report Milliken et al 2012 to CITES 16th Conference of the Parties used the methods described in this report to estimate trends in the illegal ivory trade from 1996 to 2011. The results were presented using a number of different indices and further analysis as described below.

4.1 Direct summaries of the Transactions and Weights Indices

The Transactions Index was summarised in a number of ways: the means and 90% credible intervals were shown for each ivory class and each year. For each ivory class the 1998 value was set to 100 so that comparisons within the ivory class could be made over time. The year 1998 was chosen because this was the first full year after ETIS was set-up and the first tightly regulated sale of ivory from three African countries to Japan was allowed following a full-scale ban on the legal ivory trade since 1989.

Global values of TI and WI were shown with 90% credible intervals. Again, for each index the 1998 value was set to 100.

To compare the relative contribution of each ivory class a bar-plot showing the mean contribution of each ivory class to the global mean for each year was calculated. This was done separately for the WI and TI. The 1998 global mean was set to 100 in each case.

4.2 Cluster analysis

A cluster analysis was performed to identify countries with similar illegal ivory trade characteristics. The main trade characteristics of interest are the Transactions Index for the six ivory classes aggregated over 2009 to 2011. A particular feature, however, of great interest to CITES, not captured by our ivory classes is the occurrence of large-scale shipments, in this case defined as shipments over one tonne in weight. To include these seizures in the cluster analysis requires that some form of bias-adjustment should be applied to their observed numbers, just as the TIs for the six ivory classes are bias-adjusted. Since large-scale seizures were not isolated as a separate class in the modelling (there were too few for this to work), a post hoc approximate method of adjustment was sought. Using the basic factorisation of the mean number of seizures in the main model, namely $\mu_{ikt} = \lambda_{ikt}\phi_{it}\theta_{it}$ as a guide, we divided the observed number of large-scale seizures by the appropriate estimated seizure rate and reporting rate and define the bias-adjusted number $\breve{Y}_i$ and weight $\breve{W}_i$ of seizures in country i as:

$$\breve{Y}_i = \sum_{t=2009}^{2011} \sum_{j=1}^{y_{ikt}} \frac{1}{\hat{\phi}_{it}\hat{\theta}_{it}} I_{ijt} \text{ and } \breve{W}_i = \sum_{t=2009}^{2011} \sum_{j=1}^{y_{ikt}} \frac{w_{ijt}}{\hat{\phi}_{it}\hat{\theta}_{it}} I_{ijt}\text{ , where } I_{ijt} = 1 \text{ if } w_{ijt} \geq 1000\text{;}$$

$\hat{\phi}_{it}$ and $\hat{\theta}_{it}$ are the posterior means of the seizure and reporting rates, respectively, from the main model.

A criticism of this bias-adjustment is that a zero number of seizures over one tonne would map to zero in the adjustment, and this may not be realistic.

The cluster analysis took account of information about countries that were implicated in illegal ivory seizures but did not make any seizures themselves. In previous CoP analyses (Milliken et al, 2002, 2004, 2007, 2009) this was represented as the number of seizures, or total weight of seizures, in which a country was implicated. Here we needed to bias-adjust these numbers in a similar way to the number of bias-adjustment above. A difference for these seizures is that the bias-adjustment is based on the country where the seizure occurred and not the country that is implicated in the seizure. So the bias-adjusted numbers and weights become

$\breve{Y}_i^* = \sum_{t=2009}^{2011} \sum_{m \neq i} \sum_{j=1}^{y_{mkt}} \frac{1}{\hat{\phi}_{it}\hat{\theta}_{it}} I_{imjt}$ and $\breve{W}_i^* = \sum_{t=2009}^{2011} \sum_{m \neq i} \sum_{j=1}^{y_{mkt}} \frac{w_{mjt}}{\hat{\phi}_{it}\hat{\theta}_{it}} I_{imjt}$ where $I_{imjt} = 1$ if $w_{mjt} \geq 1000$ and country i is implicated in the seizure.

Together we have ten variables as inputs into the cluster analysis: the TI values for the six ivory weight classes, adjusted numbers and weights of large-scale seizures, and adjusted numbers and weights of seizures made in other countries. The variables, transformed to a log scale were used in a cluster analysis using the Euclidean metric and Ward's clustering method (Everitt et al, 2001). The interpretation of the clustering, and the number of groups chosen, were determined by TRAFFIC International.

5. Results

We implemented the methodology on all valid seizure records from 1996 to 2011 that were met ETIS's standards for data analysis on (give date*). This gave 11,633 records of illegal ivory seizures. Only 47% of these records reported the weight of the seizure so the weights of the remaining 53% of records were estimated using the model described in section *. Given the estimated weights we used the criteria described in section * to select the data for the main analysis. Although 88 countries reported at least one seizure from 1996 to 2011, we excluded 28 countries that did not meet the criteria and included an additional eight countries that made no seizures themselves but met the criteria because they were implicated in seizures. Thus our dataset for modelling the number of transactions contained information on 11,857 seizures of which 3,815 were seizures of raw ivory and 8,042 were seizures of worked ivory giving 11,857 seizures in total, see table 1. Our model of the weight per seizure was obtained by fitting data to 2,470 raw ivory seizures and 3,228 worked ivory seizures which recorded the weight of a seizure.

The key results, the Transactions and Weights Indices and the results of the cluster analysis are presented in Milliken et al 2012. In the Appendix of this report we present the parameter values from fitting each of the three models described in tabular and graphical form as appropriate.

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Appendices: Tables and Graphs of results from model fitting

Estimating weights of seizures from number of ivory pieces

Table 1: Details of polynomial regression model

		Degree of polynomial (and *P*-value)		
	α	**ln*(#pieces)***	***Year***	R^2
Raw	0.105	9 ($P < 0.0001$)	6 ($P = 0.01$)	68.1
Worked	0.04	5 ($P < 0.0001$)	4 ($P = 0.01$)	33.4

Estimating the number of transactions

Table 2: Number of seizures by ivory class used in the model to estimate the number of transactions

	Weight class			
Type	[0,10)	[10,100)	[100,)	Total
Raw	2,183	1,346	286	3,815
Worked	7,567	429	46	8,042
Total	9,750	1,775	332	11,857

Table 3: Posterior means of the coefficients of the standardized proxy predictors for seizure and reporting rates.

Variable	Predictor (standardized)	Posterior mean	95% credible interval
Seizure rate, ϕ	Lagged LE ratio, *LE1*	0.766	(0.471, 1.074)
	Rule of law, *rl*	0.464	(0.067, 0.864)
Reporting rate, θ	Data collection score, *dc*	2.521	(2.246, 2.817)
	CITES reporting score, *rep.sc*	0.733	(0.520, 0.949)

Table 4: Posterior means of r before rounding

Ivory Class	**Raw**		**Worked**	
	Posterior Mean	**95% credible interval**	**Posterior Mean**	**95% credible interval**
Small	1.96	(1.52, 2.47)	1.24	(1.01, 1.49)
Medium	2.15	(1.52, 3.37)	1.52	(1.02, 2.45)
Large	1.28	(1.01, 2.01)	319.81	(1.02, 3660.00)

Table 5: Posterior means and 95% credible intervals of μ_o and μ_1

Ivory Class	μ_0		μ_1	
	Mean	CI	Mean	CI
1	0.24	(-0.37, 0.81)	-2.18	(-9.20, 4.85)
2	0.02	(-0.59, 0.57)	2.61	(-3.3, 9.08)
3	-0.63	(-1.17, -0.15)	2.60	(-2.19, 7.04)
4	0.65	(-0.20, 1.49)	8.02	(0.66,15.86)
5	-1.10	(-1.83,-0.44)	3.73	(-3.2,10.27)
6	-3.72	(-4.98,-2.74)	1.13	(-6.97,10.41)

Table 6: Posterior means and 95% credible intervals (CI) of the random effects

Ivory Class	a_2 Mean	a_2 CI	a_3 Mean	a_3 CI	a_4 Mean	a_4 CI	a_5 Mean	a_5 CI	a_6 Mean	a_6 CI
1	-2.81	(-6.08, 0.46)	0.47	(-2.63, 3.60)	-2.66	(-5.74, 0.36)	-1.24	(-4.24, 1.66)	-2.74	(-5.59, 0.16)
2	2.27	(-1.07, 5.62)	-0.82	(-4.01, 2.45)	1.14	(-2.15, 4.40)	1.46	(-1.80, 4.71)	1.42	(-1.83, 4.63)
3	4.63	(-0.84,10.02)	1.59	(-3.76, 6.88)	3.18	(-2.28, 8.55)	-0.81	(-6.15, 4.57)	-0.80	(-6.10, 4.54)
4	-0.13	(-3.80, 3.49)	1.04	(-2.45, 4.52)	3.30	(-0.22, 6.91)	0.56	(-2.99, 4.01)	1.38	(-2.10, 4.87)
5	2.79	(-2.43, 8.05)	0.74	(-4.12, 5.84)	1.02	(-3.96, 5.97)	-2.17	(-7.08, 2.76)	-0.16	(-5.19, 4.68)
6	0.02	(-12.34, 11.93)	-0.72	(-12.62, 11.09)	0.03	(-11.52, 11.36)	-14.67	(-27.20, -3.00)	-0.37	(-11.56, 1.45)

Table 7: Posterior mean and 95% credible interval for Ω_0

Ivory Class	1	2	3	4	5	6
1	4.20 (2.60, 6.54)					
2	2.30 (1.09, 4.00)	4.12 (2.58, 6.45)				
3	0.59 (-0.37, 1.76)	1.64 (0.62, 3.09)	2.56 (1.41, 4.34)			
4	2.49 (0.68, 4.96)	1.55 (-0.24, 3.82)	0.30 (-1.19, 1.92)	10.88 (7.22, 16.34)		
5	1.82 (0.48, 3.64)	2.11 (0.75, 4.01)	1.44 (0.32, 2.97)	2.60 (0.58, 5.42)	5.11 (3.03, 8.26)	
6	1.29 (-0.27, 3.33)	2.06 (0.48, 4.34)	2.19 (0.80, 4.35)	1.55 (-0.74, 4.44)	2.67 (0.90, 5.43)	5.47 (2.61, 11.01)

Table 8: Posterior mean and 95% credible interval for Ω_1

Ivory Class	**1**	**2**	**3**	**4**	**5**	6
1	438 (238, 750)					
2	339 (183, 577)	279 (136, 503)				
3	178 (68, 340)	143 (51, 300)	86 (17,234)			
4	358 (18, 609)	273 (123, 479)	155.40 (48, 315)	488 (236, 860)		
5	301 (109, 556)	241 (84, 471)	130 (33, 287)	291 (120, 540)	260 (71, 560)	
6	23 (-156, 235)	14 (-126, 178)	4 (-93, 85)	26 (-150, 212)	19 (-117, 191)	29 (3, 124)

Table 9: DIC of different models.

Model	$logit(\lambda_{it})$	$log(\theta_{it})$	$log(\phi_{it})$	DIC
M_0	α_{0it}	0	0	10490
M_1	$\alpha_{0it} + \alpha_1\zeta_1(t)$	0	0	10050
M_2	$\alpha_{0it} + \sum_{1}^{6} \alpha_p\zeta_p(t)$	0	0	10500
M_3	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	0	0	10040
M_4	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	0	$\beta_1\mathrm{LE1}_{\mathrm{it}}$	10010
M_5	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	0	$\beta_1\mathrm{LE1}_{\mathrm{it}} + \beta_2\mathrm{rl}_{\mathrm{it}}$	10010
M_6	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	$\gamma_1\mathrm{dc}_{\mathrm{it}}$	0	9668
M_7	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	$\gamma_1\mathrm{dc}_{\mathrm{it}} + \gamma_2\mathrm{rep.sc}_{\mathrm{it}}$	0	9638
M_8	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	$\gamma_1\mathrm{dc}_{\mathrm{it}} + \gamma_2\mathrm{rep.sc}_{\mathrm{it}}$	$\beta_1\mathrm{LE1}_{\mathrm{it}}$	9629
M_9	$\alpha_{0it} + \alpha_{1it}\zeta_1(t) + \sum_{2}^{6} \alpha_p\zeta_p(t)$	$\gamma_1\mathrm{dc}_{\mathrm{it}} + \gamma_2\mathrm{rep.sc}_{\mathrm{it}}$	$\beta_1\mathrm{LE1}_{\mathrm{it}} + \beta_2\mathrm{rl}_{\mathrm{it}}$	9629

Note that although the DIC in the final two models is the same the 95% credible interval for rule of law (rl) did not include zero.

Estimating the weight per seizure

Table 10: Parameter estimates for weights per seizure model.

	Parameter	Posterior mean	95% credible interval
Raw:	δ_0	0.308	(0.247, 0.369)
	δ_1	-0.210	(-0.270, -0.151)
	ν	12.940	(8.862, 20.020)
	σ^2	2.679	(2.468, 2.900)
Worked:	δ_0	2.366	(2.299, 2.434)
	δ_1	0.105	(0.038, 0.169)
	ν	7.917	(5.950, 10.990)
	σ^2	2.193	(1.990, 2.408)

Table 11: Countries and Country codes included in final analysis

Code	Country	Code	Country
ae	United Arab Emirates	kh	Cambodia
ao	Angola	kp	Democratic People's Republic of Korea
at	Austria	kr	Republic of Korea
au	Australia	la	Laos
be	Belgium	ml	Mali
bi	Burundi	mo	Macao
bj	Benin	mw	Malawi
bw	Botswana	mx	Mexico
ca	Canada	my	Malaysia
cd	Democratic Republic of Congo	mz	Mozambique
cf	Central African Republic	na	Namibia
cg	Congo	ng	Nigeria
ch	Switzerland	nl	Netherlands
ci	Côte d'Ivoire	nz	New Zealand
cm	Cameroon	ph	Philippines
cn	China	pl	Poland
de	Germany	pt	Portugal
dj	Djibouti	qa	Qatar
dk	Denmark	ru	Russia
eg	Egypt	rw	Rwanda
es	Spain	sd	Sudan
et	Ethiopia	sg	Singapore
fr	France	sn	Senegal
ga	Gabon	td	Chad
gb	United Kingdom	tg	Togo
gh	Ghana	th	Thailand
gn	Guinea	tw	Taiwan
gq	Equatorial Guinea	tz	Tanzania
hk	Hong Kong	ug	Uganda
id	Indonesia	us	United States of America
in	India	vn	Viet Nam
it	Italy	za	South Africa
jp	Japan	zm	Zambia
ke	Kenya	zw	Zimbabwe

Figure 1: Posterior mean reporting rate, θ_{it}, (red), seizure rate, ϕ_{it}, (black) and combined (blue) for each country over time

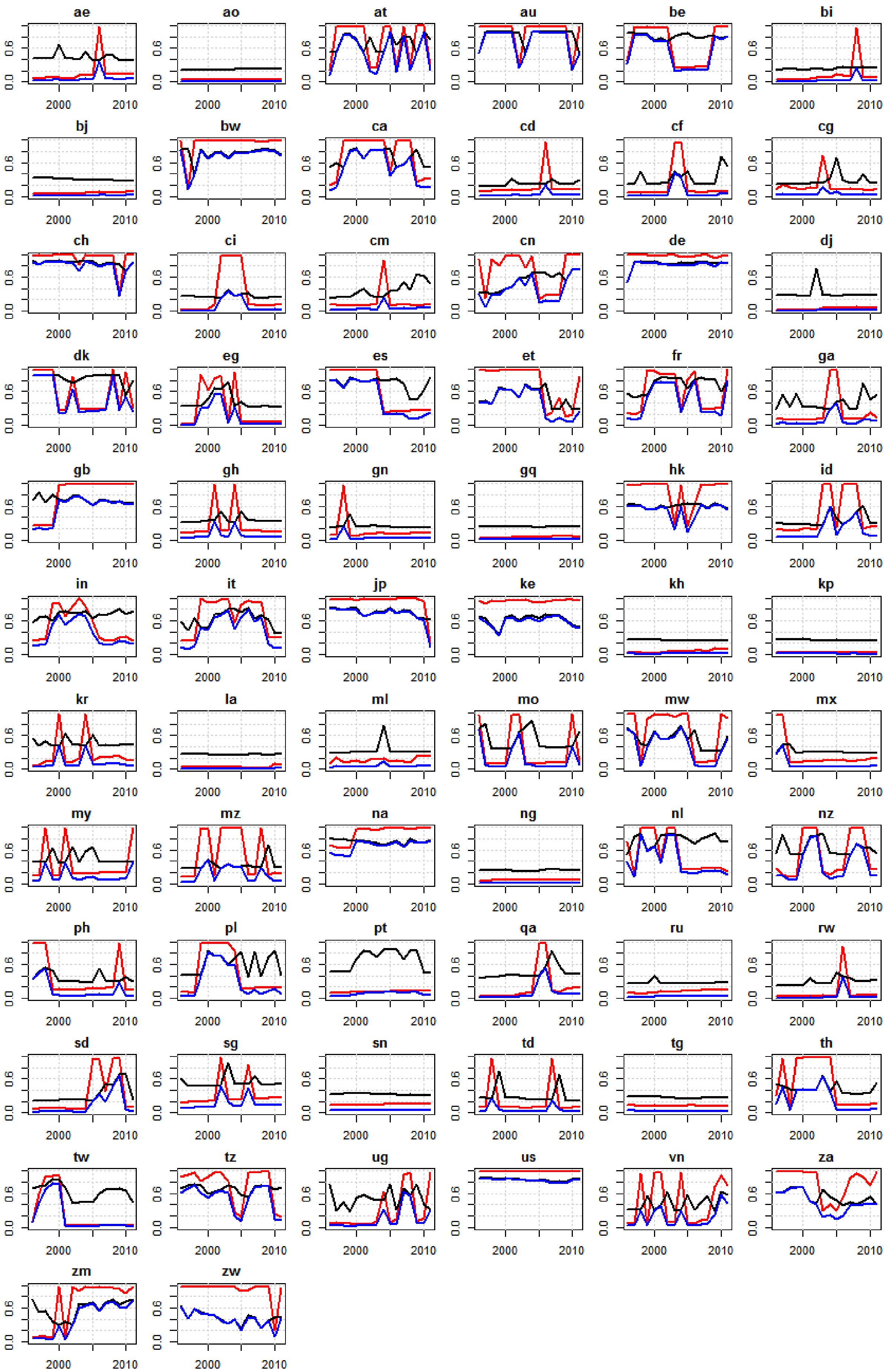

Figure 2: Posterior mean and 95% credible intervals for the random intercepts, a_{0ik}, for each country and the three raw ivory class

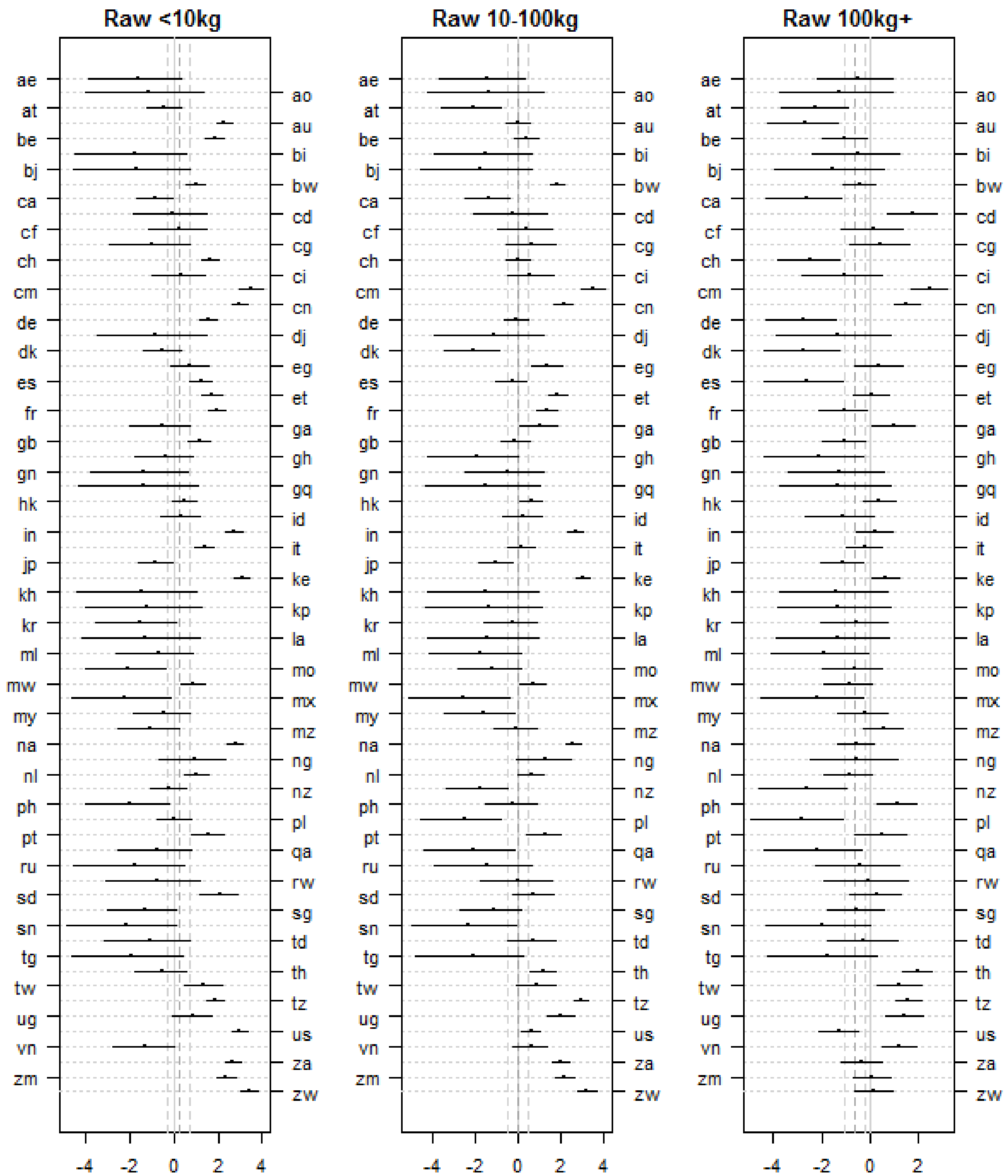

Figure 3: Posterior mean and 95% credible intervals for the random intercepts, a_{0ik}, for each country and the three worked ivory class

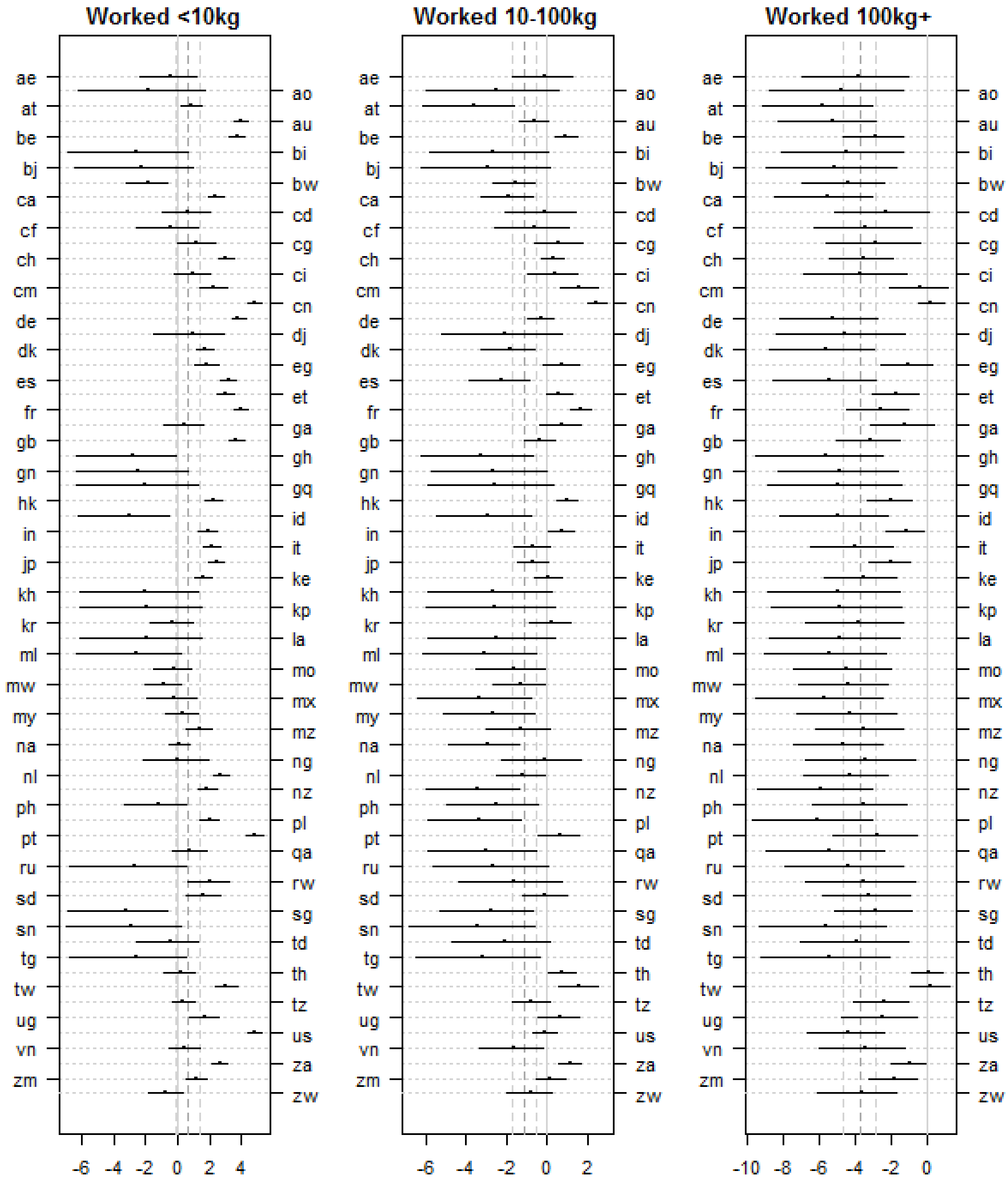

Figure 4: Posterior mean and 95% credible intervals for the random coefficients, a_{1ik}, for each country and the three raw ivory class

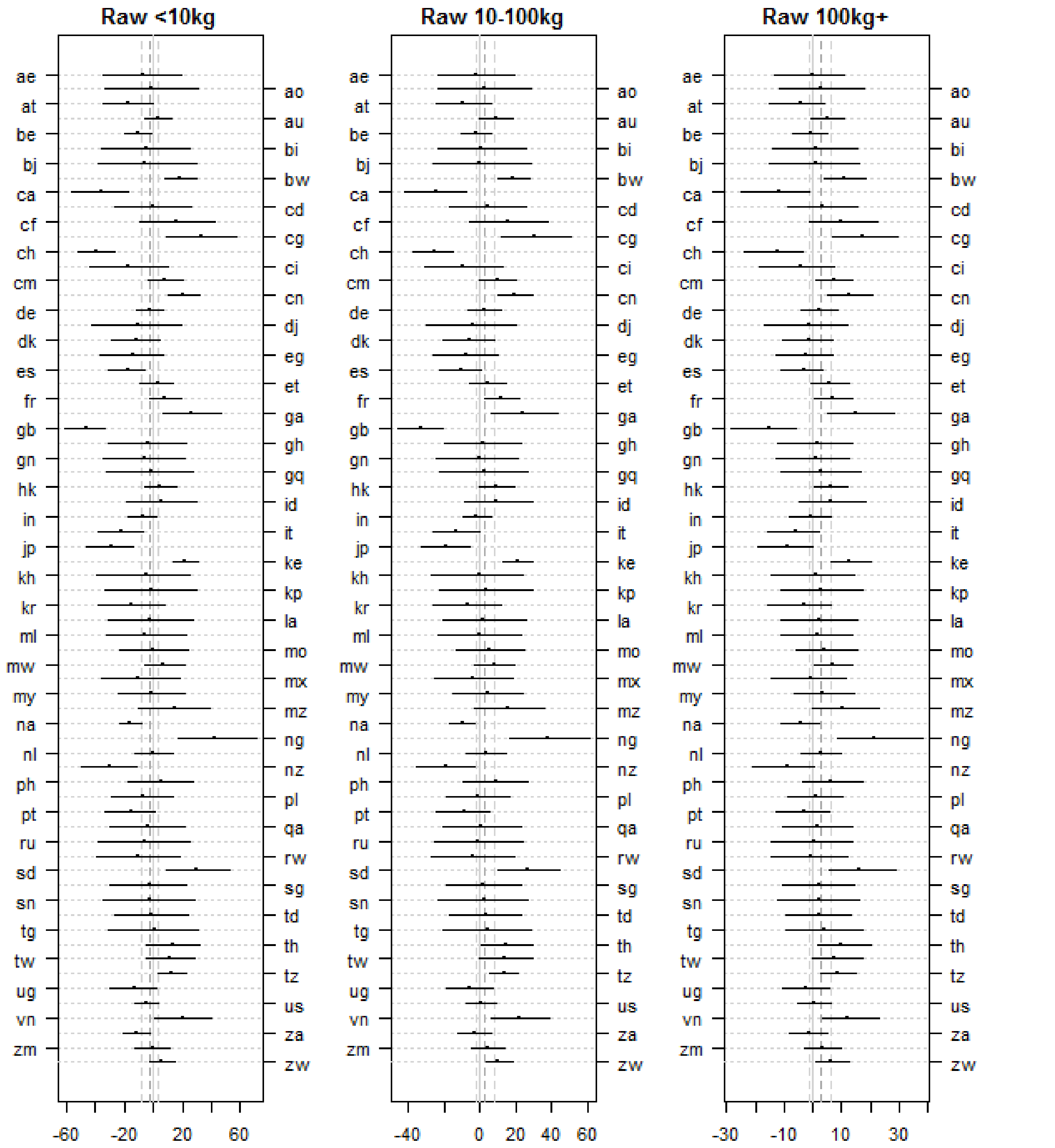

Figure 5: Posterior mean and 95% credible intervals for the random coefficients, a_{1ik}, for each country and the three worked ivory class

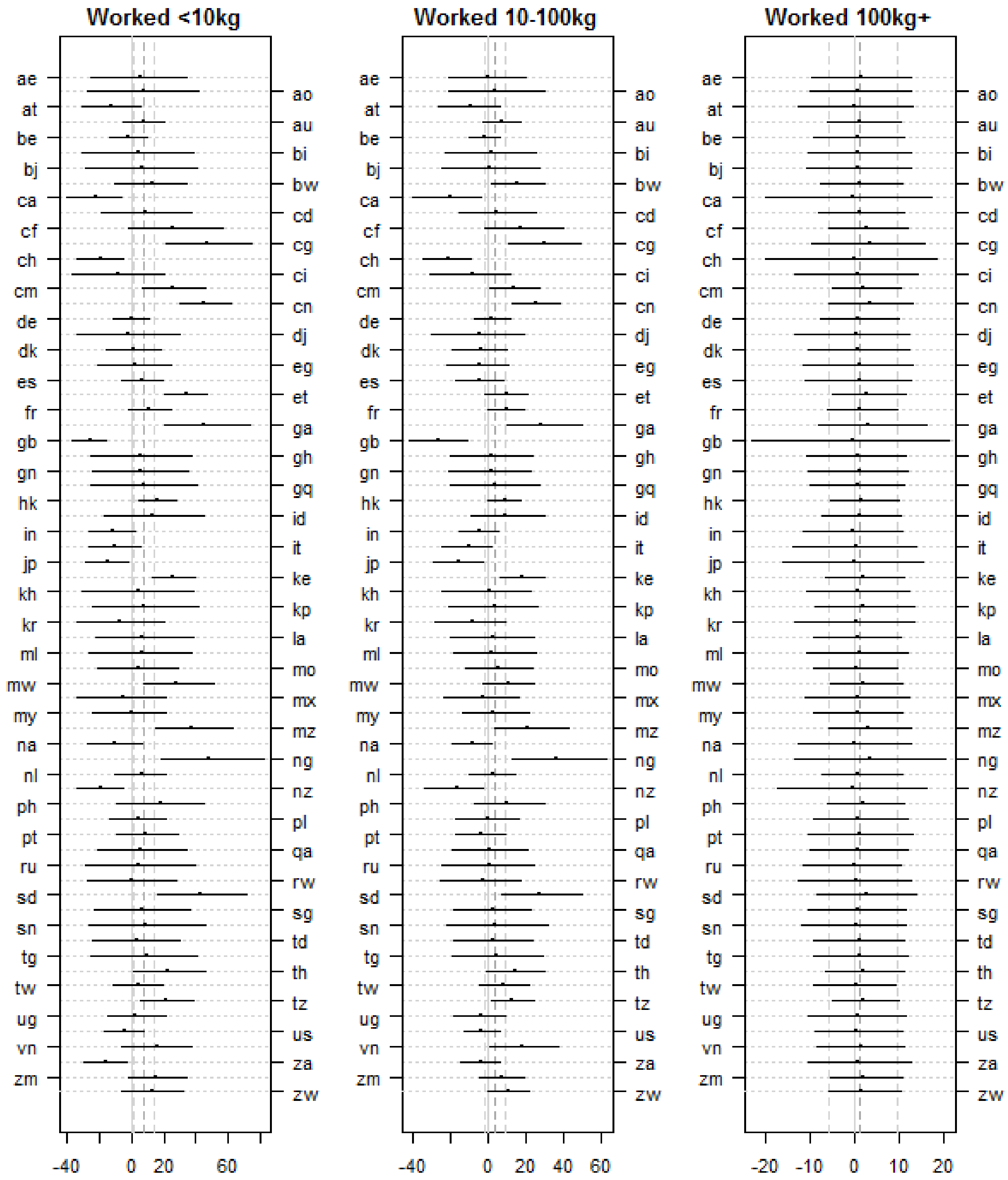

Figure 6: Number of transactions, λ_{i1t} for small raw ivory class

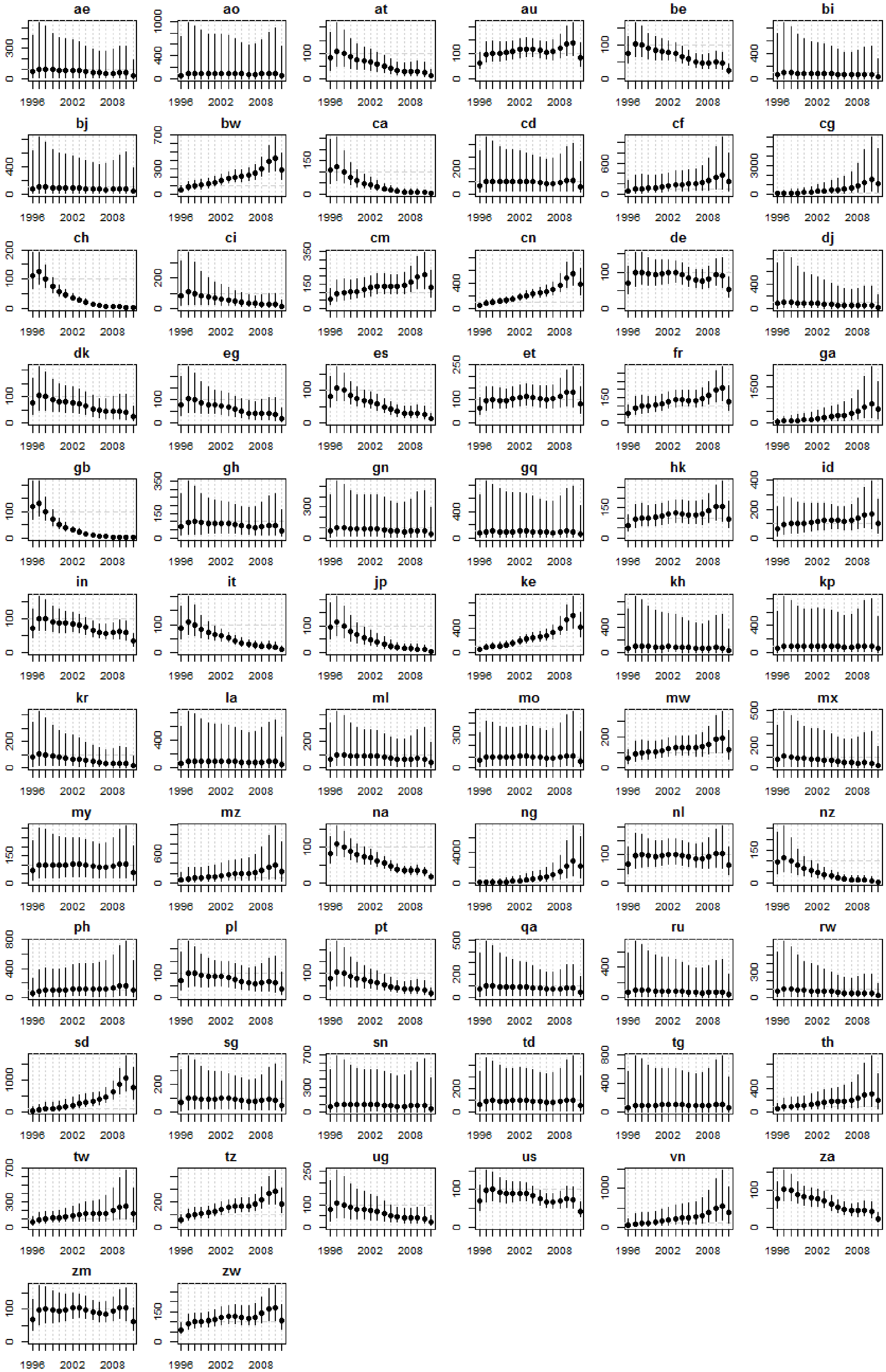

Figure 7: Number of transactions, λ_{i2t}, for medium raw ivory class (10kg - <100kg)

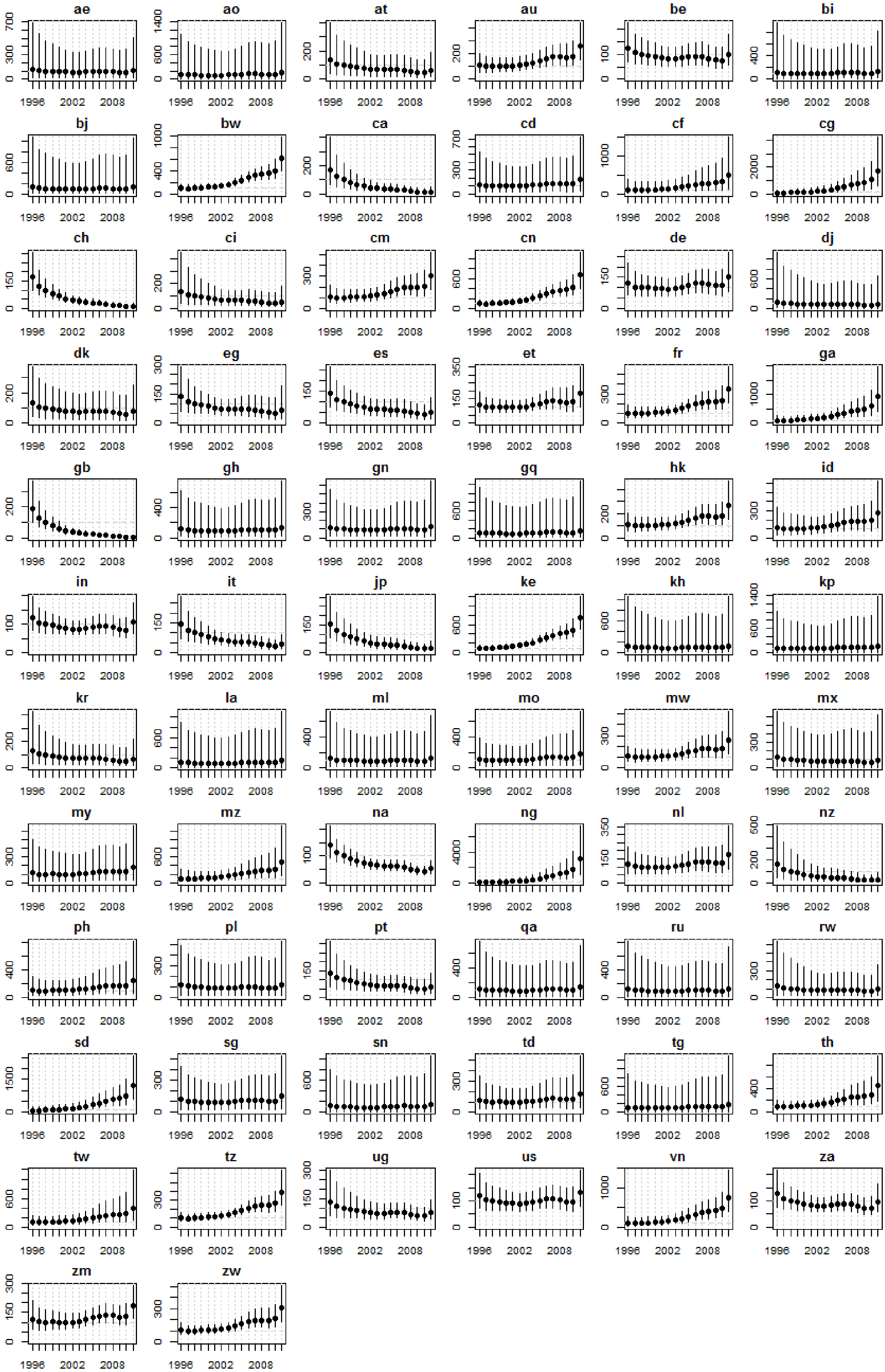

Figure 8: Number of transactions, λ_{i3t}, for large raw ivory class (100kg+)

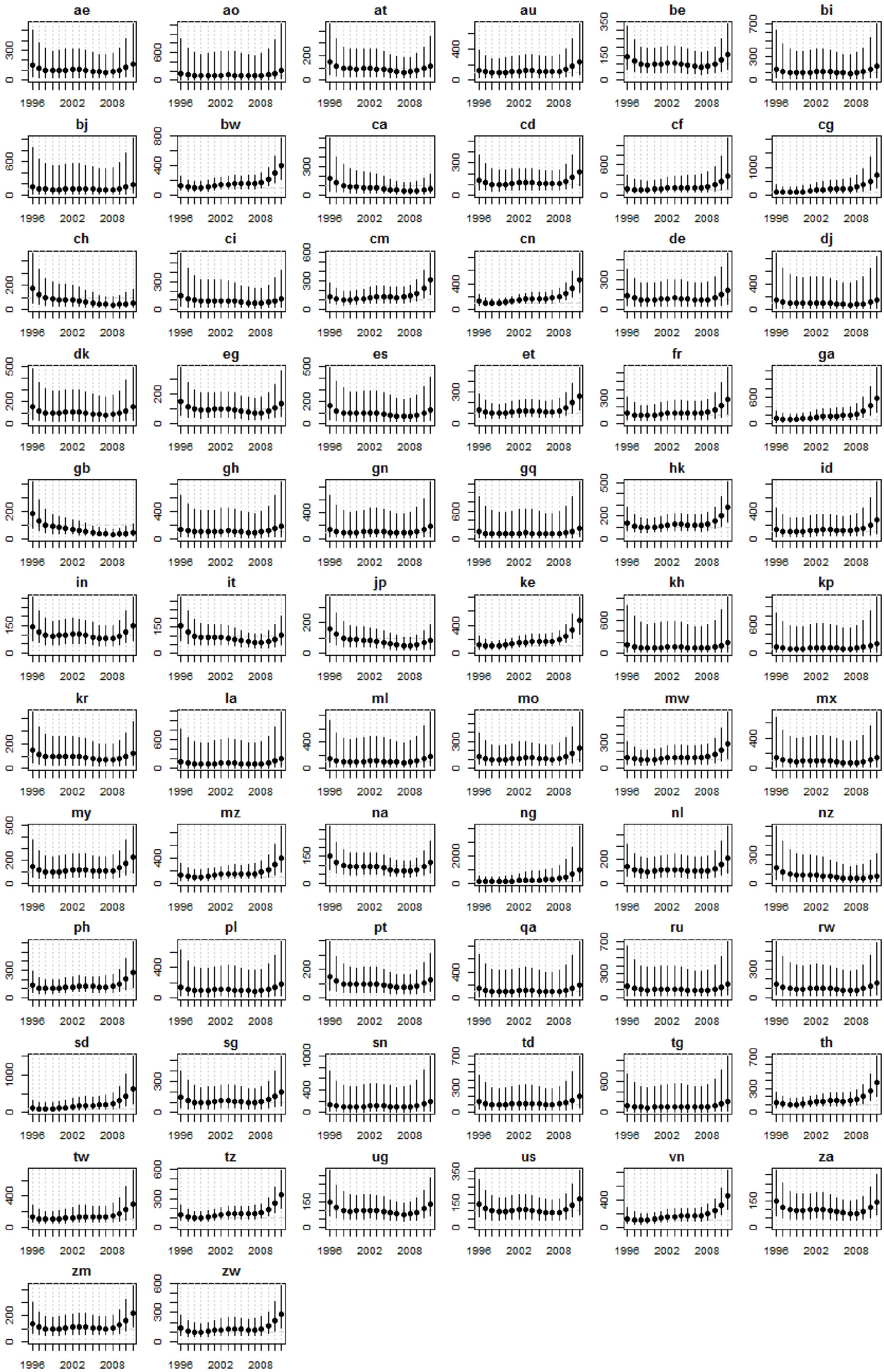

Figure 9: Number of transactions, λ_{i4t}, for small worked ivory class (<10kg)

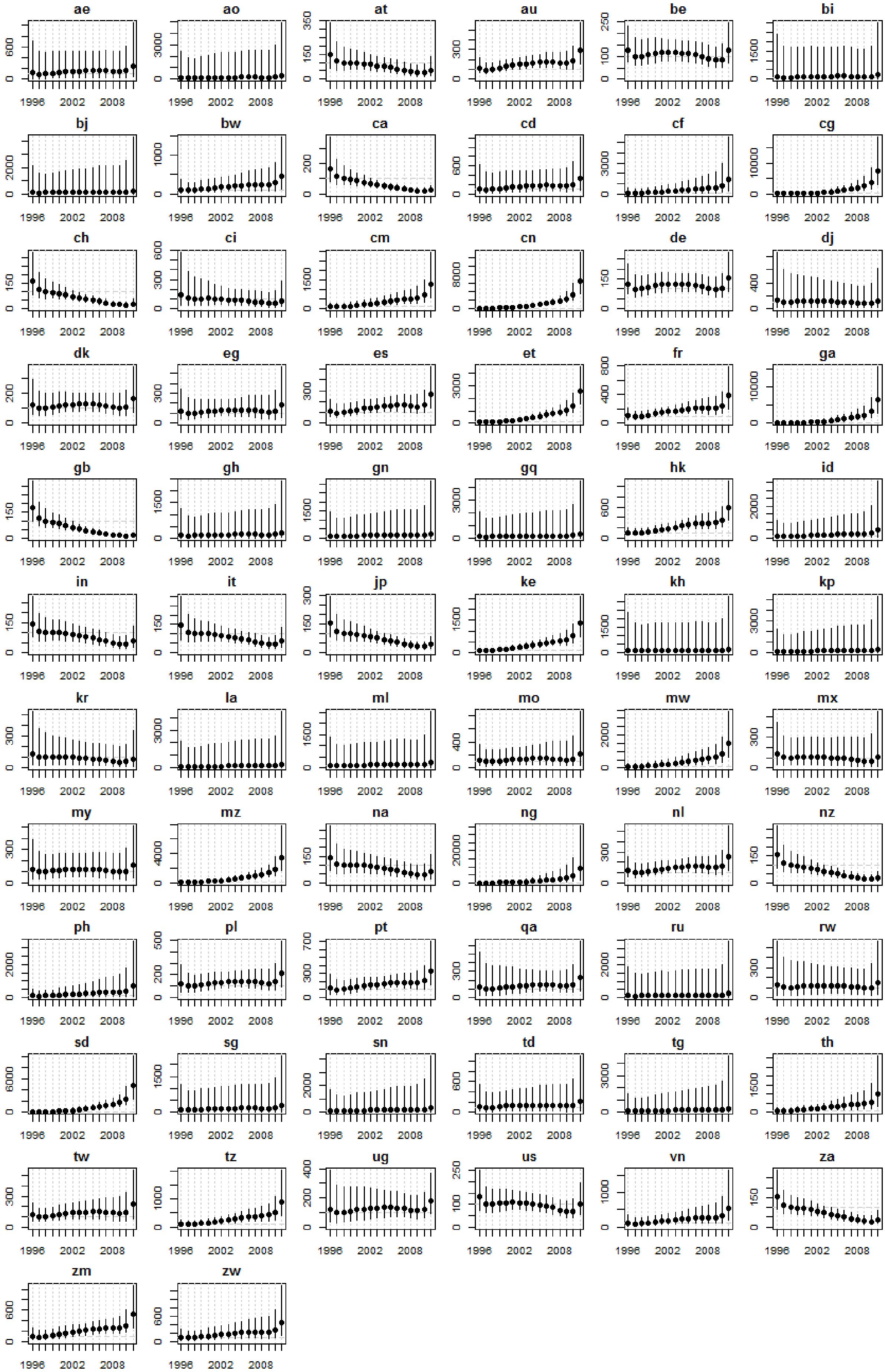

Figure 10: Number of transactions, λ_{i5t}, for medium worked ivory class (10kg - <100kg)

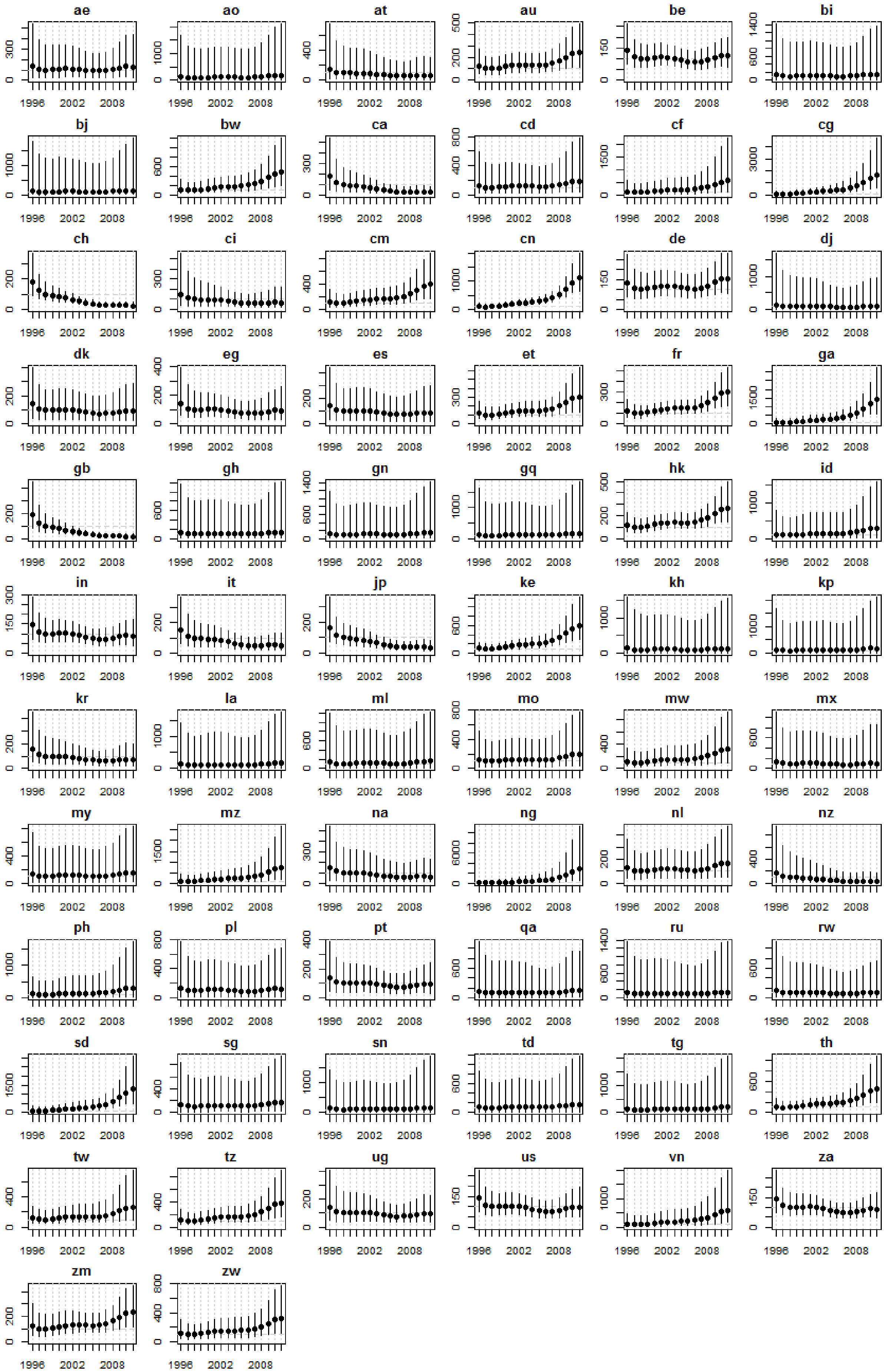

Figure 11: Number of transactions, λ_{i6t}, for large worked ivory class (100kg+)