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Market patterns within Indonesia's songbird trade

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ABSTRACT

Songbirds recorded in Indonesia's songbird trade are more than quarter of its known species. However, only a fraction (approx. 30 %) has demand records. This trade is driven by supply-demand interactions, however current research commonly focuses on either demand or supply, and not its interactions. Understanding interaction patterns is crucial to answering what drives supply and demand, information pivotal to curbing unsustainable trade. We developed an approach to identify these interaction patterns and predict key drivers of supply and demand. We focused mainly in Java, using existing research we identified types of supply and demand data and using field surveys we filled in data gaps. We created the trade interaction value (TIV) by matching species supply and demand data to assess how well supply meets demand. We clustered species into three groups based on their TIV then developed a model to predict the cluster species with supply only records belonged to. The first cluster had the highest demand and was dominated by species with traits important for songbird competitions. Small or large sized, endemic species, and those listed as vulnerable or near threatened were important for the second cluster. The third cluster had traits common of household ornamental species. We predicted that 7.7 % of supply-only species were in the market opportunistically, while the remaining followed one of the three existing cluster patterns. Our research is the first looking at songbird trade from both sides of the market and we hope that it can be a reference for similar approaches applied to other taxa heavily affected by unsustainable trade.

1. Introduction

Indonesia's songbird trade is one of the world's most prolific wildlife trade. With >300 species recorded—including protected, endangered, and endemic ones—(Chng and Eaton, 2016; Chng et al., 2015, 2016; Indraswari et al., 2020; Okarda et al., 2022), the trade's unsustainable growth is contributing to wild population decline and species extinction (Bergin et al., 2017; Eaton et al., 2015; Leupen et al., 2020; Nijman et al., 2021; Rheindt and Baveja, 2019). However, information we know about the trade mainly derive from exploring a single side of the market, either its supply (recorded through market surveys (Chng et al., 2015; Leupen et al., 2020; Okarda et al., 2022) or wildlife shipment confiscations (Chng et al., 2021; Indraswari et al., 2020), or its demand (reflected from records of species ownership (Jepson and Ladle, 2009; Marshall et al., 2020; Nuruliawati et al., 2024). The trends we can detect from a single side would suffice in providing records of species in the trade, a snapshot of the volume of individuals traded, and can assist in developing conservation strategies primarily aimed at saving species with

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rapidly declining populations and high trade volumes (Lee et al., 2016; Olivares-Rojas et al., 2024; Shepherd and Chng, 2017). However, this approach falls short when the target objective is to understand the dynamics of the entire market and highlight emerging patterns.

Developing strategies that aim for sustainability would firstly require understanding of the dynamics that exist within the market (Auliya et al., 2016; Carpenter et al., 2004; Liew et al., 2021). Market dynamics emerge from the interactions of its supply and demand (Kubo et al., 2025; Lubis et al., 2024; Sharpe, 1964); therefore, it would not be possible to gather the information needed by solely focusing on a single side of the market. Understanding interactions could additionally give way to identifying potential presence of other market trends, such as substitution effects (Huber and Puto, 1983; Oyanedel et al., 2022), opportunistic supply (Gephart and Pace, 2015; Oyanedel et al., 2022; Patel et al., 2015), and even predicting patterns that drive the trade. Using data from a single side will not only miss these patterns but would also create a risk of developing misleading interpretation of patterns (Blundell and Mascia, 2005; Challender et al., 2022; Fukushima et al., 2020; Wyatt, 2013).

Ideally, supply and demand data would need to be gathered in a comprehensive manner with a well-defined scope of time and space. Unfortunately, wildlife trade is a complex and illicit market, and quantifying patterns for is notoriously difficult (Barber-Meyer, 2010; Van Uhm and Moreto, 2018; Wyatt, 2013). Interestingly for songbird trade, there are many sources of data spanning a wide temporal and spatial scale, each containing valuable information on the condition of trade throughout a certain period (Mirin and Klinck, 2021). Ignoring the presence of such data just because of its unstructured temporal and spatial scale would be reckless as it would mean that we would be ignoring the facets of information present. Rather, we should consider the challenges in interpreting such information and accompany it with deep analytical approach, high level of comprehension, and integrative assessments while at the same time considering for potential dimensions of its limitations (Kubo et al., 2025). Being able to understand patterns from scattered data while considering the aspects mentioned, however tentative, can at least provide some snapshot to existing patterns and is better than complete ignorance of any trade dynamics (Kubo et al., 2025; Tittensor et al., 2020), especially in the light of emergent threats coming from the trade characterised by a highly dynamic and rapid shift in trends (Jepson and Ladle, 2009; Nijman et al., 2017; Shepherd et al., 2024) and species turnover (Nijman et al., 2017). With such thoughts in mind maximising the potential of existing yet limited data might even open a previously unexplored approach in wildlife trade data gathering and analysis.

To date, there has not been work on compiling and matching supply and demand data in songbirds, identifying and grouping recorded species based on emerging patterns then use them to predict existing and potential market patterns. In this paper we aim to test these possibilities. We loosely define our spatial and temporal scales, spatially we focus on Java the epicentre of songbird trade (Indraswari et al., 2020), while temporally we limit data to that from 2015 to 2022. Restricting this enough will still capture the nuance of trends that may occur during this defined time at space. Due to the various sources of data, we gathered for this work, we present the output as a blueprint of potential patterns, not to be taken at face value, rather to be taken as a proxy of potentially present patterns and guidelines for future conservation strategy development. We determine: 1) whether we can group species recorded in the trade based on both its demand and supply patterns, 2) whether we can characterise those groups based on known species traits. We also try to identify the potential presence of market phenomenon, which include 3) species present in the supply side being substitutes of ones in high demand (i.e.: the substitution effect) and suspect whether this effect contributes to the high number of species in the trade, and 4) the likelihood of opportunistic trade present in the supply side. We then explore making sense of such sparsely collected databases and provide insights into how its understanding can highlight areas that need further attention in development of future conservation and policy informing strategies.

Our approach focuses on approaching how to use information that is not complete, as what is commonly present in wildlife trade. Given that other wildlife taxa has forms of supply and demand data similar to the songbird trade (Donald et al., 2024; Gomez et al., 2023; Hughes et al., 2023; Toomes et al., 2022), we hope our work can be an example on how to predict market trends for other taxa and could support provision of information needed to help reduce the pressure of unsustainable wildlife trade globally.

2. Method

2.1. Study site and data gathering

We did a rapid search using Google Scholar and keywords “songbird trade”, “songbird market”, “songbird ownership”, “songbird pets”, “songbird confiscation”, “songbird seizure”, and “songbird survey” in both English and Bahasa Indonesia to identify papers published that had data on supply or demand surveys from years 2016 to 2022. We did this to identify the types of market data available in the literature as well as acquire a baseline on the number of species found in the trade. We gathered publications that conducted supply or demand side surveys that did not specifically target a bird taxon to allow a non-biased approach in recording data. The publications we found are listed in Supplementary Material A.

We gathered information from entire Indonesia to identify the number of species recorded in the trade, but we spatially focused our work identifying market patterns to Java, the epicentre of the songbird trade (Eaton et al., 2015; Indraswari et al., 2020). For supply, we used records of species found being sold in the physical markets and records of species confiscated throughout the trade chain from areas Indonesia-wide but were destined for Java. The latter we call train chain supply, and used the media reports dataset from Indraswari et al. (2020) that identified songbird trade chain routes and hotspots. Wildlife illegally shipped throughout the trade chain would be confiscated by authorities, mainly due to lack of permit for shipment and details of origin of species, and are often individuals illegally harvested from the wild (Siriwat and Nijman, 2018; Tittensor et al., 2020).

Both supply sources presented records species presence as well as its abundance, therefore this was the data used in this research (Table 1). We found some papers published after 2020 that listed species sold online; we did not include this information for supply because we could not confidently determine that the location of sellers in the online surveys was in Java.

Availability of published demand data was scarcer than supply. From literature in our time frame, the data we found representing demand was on household species ownership. Ownership represents a fulfilled demand (Bush et al., 2014), ideal for comparing whether supply pattern matches known demand. We conducted field surveys to supplement the data on this demand side. We added information on household ownership and provided distinct information on ownership by competition goers (competition ownership). We also added information on desired species, representing potential market demand, and best-selling species, indicating species with high demand (Pantić et al., 2021). Information on demand was gathered from consumers surveyed at households and at competition venues while information on best-selling species was collected by surveys from market and store vendors. We recorded species presence and abundance for demand from household and competition ownership. For desired and best seller species however, we recorded a mention of a single species by a participant as a single presence (Table 1).

Field work for gathering demand data was conducted from July to November 2019 and field data was derived from surveys conducted in all six provinces in Java, with 48 household surveys (totalling 288) and 144 competition surveys (totalling 864) for each province. Surveys were

Table 1
Source and definition of supply and demand data.

Data type	Source of data	Description	Measure	Survey location and source of data
Supply data	Market	Species recorded from market surveys.	Richness and Abundance	Jakarta (Chng et al., 2015); West Java (Iskandar et al., 2019; Cahyadi, 2018; Chng et al., 2016; Haryoko, 2010); Central Java, Yogyakarta, and East Java (Chng and Eaton, 2016)
	Supply chain	Confiscated species *en route* to Java that were published on online news.	Richness and Abundance	Whole of Indonesia (Indraswari et al., 2020) destined for Java (see Supplementary material B)
Demand data	Household ownership	Species ownership recorded from household surveys	Richness and Abundance	(Marshall et al., 2020) and field survey (consumers)
	Competition ownership	Species ownership recorded from competition surveys	Richness and Abundance	Field survey (consumers)
	Desired birds	The top three species desired by keepers surveyed in competitions.	Presence/ absence (Species mention was recorded as presence)	Field survey (consumers)
	Bestselling birds	The top three species are considered by sellers as bestselling species.	Presence/ absence (Species mention was recorded as presence)	Field survey (sellers - market and stall vendors)

completed by 1152 songbird consumers (192 consumers for each province). The survey was Participants in each of these surveys (n = 1152) were asked about species ownership as well as their top three desired species.

Data on bestselling species were gathered from vendors. We randomly selected vendors from the same bird markets in Jakarta, Western, Central, and Eastern Java as well as Yogyakarta, where the market surveys from studies listed in Table 1 were conducted. On top of vendors in markets, we also randomly selected vendors as we traversed neighbourhoods within each province, en route visiting songbird markets and households for consumer surveys. We surveyed 30 vendors in each province, totalling 180 vendors for Java. A complete method on how each location was chosen, as well as a list of the chosen sites can be found in the supplementary material.

The research was part of a larger project and the ethics for the project and its fieldwork was approved under QUT Human Research Ethics clearance under the number 1900000429, with permission for surveys granted from administration of each survey area, market, stalls, and competition organisers. Participants were given an information sheet prior to the interview that listed details about the research and survey as well as request for consent. Participants verbally provided consent to participate in the research prior to the survey. The consent form, the complete survey sheet used for this research are listed in Appendix F and H inside Indraswari (2021). The location of surveys are listed in Appendix C.

2.2. Calculating supply-demand interaction values

Since direct comparisons were difficult when using secondary research and field survey data, our designed measure is aimed to also serve as a proxy for species supply-demand interactions. We developed this measure using species recorded to have at least one of our two measures of supply (market supply and trade chain supply) as well as at least one of our four measures of demand (household ownership, competition ownership, desired species, and best-selling species) (Table 1). From here on, we would classify these species as "labelled species", because they would be labelled an interaction measure originating from recorded supply and demand data. We distinguish them from "unlabelled species", which were species that only had supply data.

The units of measurements used for each of the datasets we gathered were different, therefore we first need to transform the data to allow comparison. We transformed species supply and demand records to a scale ranging from 0 (no trade) to 1 (the highest recorded level of trade (Table 1). This transformation allows for a rank-based comparison across different measurements rather than their absolute values, making the data more comparable. The closer a normalized value is to 1, the higher the trade volume and rank, and vice versa. We mention these values as relative supply and demand values.

Once the supply and demand data for each species are transformed, we paired each of the species two supply records with each of their four demand records, resulting in eight supply-demand pairings (market-household ownership, market-competition ownership, market-desired species, and market-best-selling species, and the same four pairs with trade chain). If a species was recorded present in only one supply measure (market or trade chain) data or not in all demand measures, then the missing supply or demand record for that species would be listed as zero, and this would be the value paired with its supply or demand counterpart.

We named our proxy of species' supply and demand interaction the 'Trade Interaction Value' (hereafter, TIV). With two sources of supply, the value will compare the relative value of each species supply to each of its relative demand measure. Our TIV was calculated using the following formula:

$$\text{Trade interaction value (TIV)} = 2^{*}\left(\frac{\text{supply value} - \text{demand value}}{\text{supply value} + \text{demand value}}\right)$$

We multiplied with the value of 2 considering that we recorded two sources of supply. Multiplying the values by two will broaden the range of TIV allowing a more extensive understanding of its values. With this formula and given that all values range from 0 to 1, TIV values fall within a range of −2 to 2. Matching supply with demand can result in three possible outcomes:

1. **Positive TIV**: Relative supply value exceeds its relative demand value
2. **Negative TIV**: Relative demand value exceeds its relative supply value
3. **Neutral TIV (0)**: Proportion of relative supply and demand is balanced.

The closer a TIV value is to zero, the more balanced is its supply-demand dynamics while higher values (positive or negative) indicate greater imbalance. A TIV of −2 indicates no recorded supply, while a TIV of +2 indicates no recorded demand. A complete list of all calculated TIV is in Supplementary Material E.

2.3. Data analysis: identifying species grouping based on trade interaction values

We used k-means to determine how and whether species would cluster into groups based on their eight calculated supply and demand

TIV patterns. K-means requires a pre-specified number of clusters (k) prior to performing its clustering analysis, and therefore we need to first ensure the k value selected is optimal for clustering species based on its TIV patterns. We determined this value using the NbClust function from the NbClust package (Charrad et al., 2014). NbClust iteratively evaluates outputs from 30 different algorithms to identify the most suitable number of clusters. The NbClust output suggested $k = 3$ as the optimal grouping. We visualized the clustering results using a Principal Component Analysis (PCA) ordination to explain the clustering structure and enhance pattern interpretability.

We did all of our data analysis using R version 4.4.0 (R Core Team, 2024), with K-means clustering and PCA ordination plotting done using the Factoextra (Kassambara and Mundt, 2017) and FactomineR (Lê et al., 2008) packages in R.

2.4. Determining traits and patterns that characterise species grouping patterns

We treated the identified clusters as a proxy for existing species groupings in the trade that are shaped by its underlying supply and demand patterns. We developed a predictive model to assess how well species traits can be used to characterise and even predict the cluster to which a species belongs. We developed our predictive model using random forest. We chose Random Forest due to its popularly and flexibility for smaller-scaled data. Random forest has also been used previously in songbird trade research (Marshall et al., 2020). We performed random forest using the randomForest package (Liaw and Wiener, 2007) in R.

The higher the model's accuracy in predicting a species' cluster membership, the better its performance and the greater the likelihood that species traits meaningfully characterise that cluster. We determined that an accuracy of at least 80 % is reflective of a good performing model. Predictive models assess accuracy through classification performance derived from two distinct datasets: the training dataset and the testing dataset. The training dataset serves as the foundation for predictive model algorithm, it identifies underlying patterns derived from species traits that enable the prediction of species into cluster classifications. Subsequently, the testing dataset evaluates the model's effectiveness in classification. Both datasets were subsets from our full dataset, we used 80 % of our labelled data as our training dataset and 20 % as our testing dataset. If the model performs with satisfactory accuracy (over 80 %), we moved to the next step, which is determining the importance of each trait in characterising TIV clusters.

We used Random Forest to acquire information on the importance value of each of the variables used to predict classification. These outputs however are neutral in direction, meaning we do not know whether it is the presence or absence of a trait that would characterise a cluster. Therefore we determined the direction of each variable using partial dependent plot function from the edarf package (M. Jones and J. Linder, 2016) in R. Traits that had positive values supported classification of a species into a TIV group, and negative values indicated the opposite.

Species traits are known to drive wildlife trade dynamics and contribute to exploitation and extinction risk (Hughes et al., 2023). Therefore understanding the relationship between species traits and supply-demand patterns can give insight into market dynamics (Hughes et al., 2023; Toomes et al., 2022). We chose five traits, known to have influence in driving demand, to characterise TIV clusters. The traits were species (1) mimicry ability, (2) body size, (3) taxonomy, (4) endemism, and (5) conservation status.

The first trait, mimicry ability, is a trait important for songbird keepers that participate in songbird competitions. As its name suggests, songbird competitions are events that compete pet songbird's singing abilities. This highly popular culture is predicted as one of the largest drivers of population decline and species extinction, as spending for songbird economic activity is projected to reach USD 366.8 million. The diversity of a bird's song repertoire (acquired naturally or through mimicry) is an important component in determining the winner of singing competitions (Turut, 2012). Therefore, strong mimics are popularly used in competitions.

We categorised mimicry abilities as either a flexible mimic, an incidental mimic, or having no (or no recorded) mimicry abilities, based on Goller and Shizuka (2018). Flexible mimics have stronger mimicry ability than incidental mimics, and can frequently imitate a range of sounds, usually under natural conditions. On the other hand, Incidental mimics only mimic sounds under rare circumstances. They are more likely mimic songs of heterospecifics, but less likely to mimic non-biological sounds (Goller and Shizuka, 2018). We ranked our values that record species mimicry abilities as '0' for no mimicry, '1' for incidental mimics, and '2' for flexible mimics.

The second trait was body size, a feature that influences demand for certain species (Blakey, 2009; Turut, 2012), especially with a recent identified interest for smaller songbirds. Size seems to create niche-markets (Indraswari et al., 2020; Santoso, 2021), although lately only interest for smaller sized species have been emerging, we would like to see whether there is a possibility of influence of other body size classes to emerging species groupings. Therefore, we used this trait and ranked species based on body size, where we would record small species (body mass < 50 g) as '0', medium species (body mass 51–100 g) as '1' and large species (body mass > 100 g) as '2'.

The third variable was taxonomy, because there is varying demand for different taxonomic groups. Some species and their families are particularly favoured in competitions, leading to higher popularity among consumers (Dewanto and Sitanggang, 2009; Turut, 2012; Widianto, 2019). Despite existing knowledge of these preferences, we aimed to assess the influence of taxonomy without prior assumptions. We represented taxonomic traits using the species' family. A family was classified as a distinct taxonomic category if it contained more than two species; otherwise, it was grouped under "Other." This resulted in the following groups: leafbirds (*Chloropseidae*), tailorbirds (*Cisticolidae*), finches (*Estrildidae*), laughingthrushes (*Leiothrichidae*), old-world flycatchers (*Muscicapidae*), sunbirds (*Nectariniidae*), bulbuls (*Pycnonotidae*), and starlings or mynas (*Sturnidae*). The number of species in each group is provided in Supplementary Material C.

The fourth and fifth trait was endemism and conservation status. These two traits (being endemic and of higher conservation status) correlate with rarity which is known to increase demand (Veblen, 2009). Endemicity was recorded using a binary classification of '1' for endemics and '0' for non-endemics. While for conservation status, species were ranked based on their listing in the IUCN red list, ranging from 0 to 4, where '0' represented least concern and '4' represented critically endangered.

2.5. Predicting presence of substitution effect and opportunistic supply

We used our predictive model to predict the classification of unlabelled species into one of the three identified TIV clusters based on their species traits. This means that we can predict existing demand patterns likely catering to supply-only (unlabelled) species. Random forest additionally provides this output with the probability each species would likely belong to a TIV cluster. We set a 0.51 threshold for predictions, ensuring that a species is predicted to belong to a cluster only if there is more than a 50 % chance that a species would belong to that cluster (we set an extra 0.1 as a buffer). This is based on the probability theory, with no prior assumption to a grouping, it is logical to assume equal 50–50 probability (Jaynes, 2003). We also set that probabilities that range 0.51–0.75 were classified as moderate probability and over 0.75 as high probability. Otherwise, if the probability is lower than the threshold, we consider that there is <50 % probability that the species share traits with any of the clusters and therefore could be in the trade opportunistically.

We predict that species that belong into a cluster with mid or high probability indicate similarity in traits within demand species and

therefore indicating presence of the substitution effect. The higher the probability of belonging into a cluster, the more similarities in traits and therefore the higher potential a species can become a market substitute. Lower probabilities are signs that the species does not share a lot of traits with identified supply demand patterns and therefore it has a better likelihood of being in the trade opportunistically.

We present our results by naming the identified species at family level, without revealing the species' identity because such information could potentially be misused to further fuel trade. Summarised information on the trait values within each cluster can be found in Supplementary Material C.

3. Results

We identified at least 332 recorded species in Indonesia's songbird trade (Cahyadi, 2018; Chng et al., 2018a; Chng et al., 2018b; Haryoko, 2010; Iqbal, 2015; Iskandar et al., 2019; Juhardiansyah et al., 2019; Mulyana et al., 2019). We present the list in Supplementary A. From that, 267 species were recorded in Java, with 262 (98.1 %) found in the supply side, and 74 species (27.7 %) in the demand side. We identified 67 species recorded as owned by households, 36 owned by competition participants, 27 recorded as most desired and 26 recorded as best sellers. Of the total, 69 (25.8 %) species were both in supply and demand, 193 (72.3 %) were in supply without any demand, and five (1.9 %) were in demand without any supply. The latter species were not considered in further analyses.

3.1. Species grouping patterns

We averaged the relative supply and demand measures for all the species within each of the three clusters. Species in Cluster 1 exhibited high relative demand across all measures. For supply, species in Cluster 2 had the highest relative trade chain supply values and Cluster 3 the highest relative market supply values. We coded each species and provided detailed supply and demand values in Supplementary Material D.

The Principal Component Analysis (PCA) plot captured 49.6 % of the variance along Dim1 and 23.4 % along Dim2. Fig. 1 highlights different supply and demand patterns for each cluster. The PCA plot reveals clear separation between TIV clusters without overlap (Fig. 2). Cluster 1 was plotted opposite from the direction of the TIV variables, indicating that this cluster tended to have mostly negative TIV values and that it has higher relative demand compared to its supply. This also aligns with Fig. 1 where Cluster 1 had higher relative demand values.

Cluster 2 species were plotted in the direction of Trade-chain TIVs (Fig. 2) indicating that species in Cluster 2 have positive TIVs that are positively correlated to relative trade-chain supply values. Cluster 2 species were plotted away from the market TIVs, however was not plotted in a negative direction. This indicates the cluster having weaker positive correlation with market TIVs compared to the trade chain TIV (Fig. 2). Cluster 3 was plotted lower of the PCA in a strong positively correlated direction with market-TIV vectors, indicating positive and higher market supply TIVs. The complete TIV values for all the clusters and species can be found in Supplementary Material E.

3.2. Species traits driving species interaction patterns.

Our Random Forest model demonstrated a 92 % accuracy rate in classification of species into the three TIV clusters based on its traits. The important variables differed for each cluster (Fig. 3). For Cluster 1, the most important variable was mimicry ability, with flexible mimics being the most significant followed by incidentals and non-mimics. Body size followed in importance, with medium-sized species being the most important, followed by small and then large-bodied species. Endemism also played a role, though negatively correlated, indicating that non-endemic species were more likely to belong to Cluster 1. Conservation status was not a critical factor for classifying species into Cluster 1, but when relevant, critically endangered and endangered species were notable. The most important families for Cluster 1 were families popularly used in competitions (Indraswari et al., 2020; Turut, 2012), such as Muscicapidae, Leiothrichidae, and Chloropseidae, respectively.

For Cluster 2, the most important trait was bird size, with large and small birds having similar importance. Population status was next, with vulnerable, near threatened, and endangered species being important, respectively. Mimicry ability followed, ranking with incidental mimics, non-mimics, and flexible mimics. Endemism was positively significant and the key families for Cluster 2 were Pycnonotidae, Sturnidae, Cisticolidae, and Chloropseidae, respectively.

In Cluster 3, bird size remained the most important trait (with large

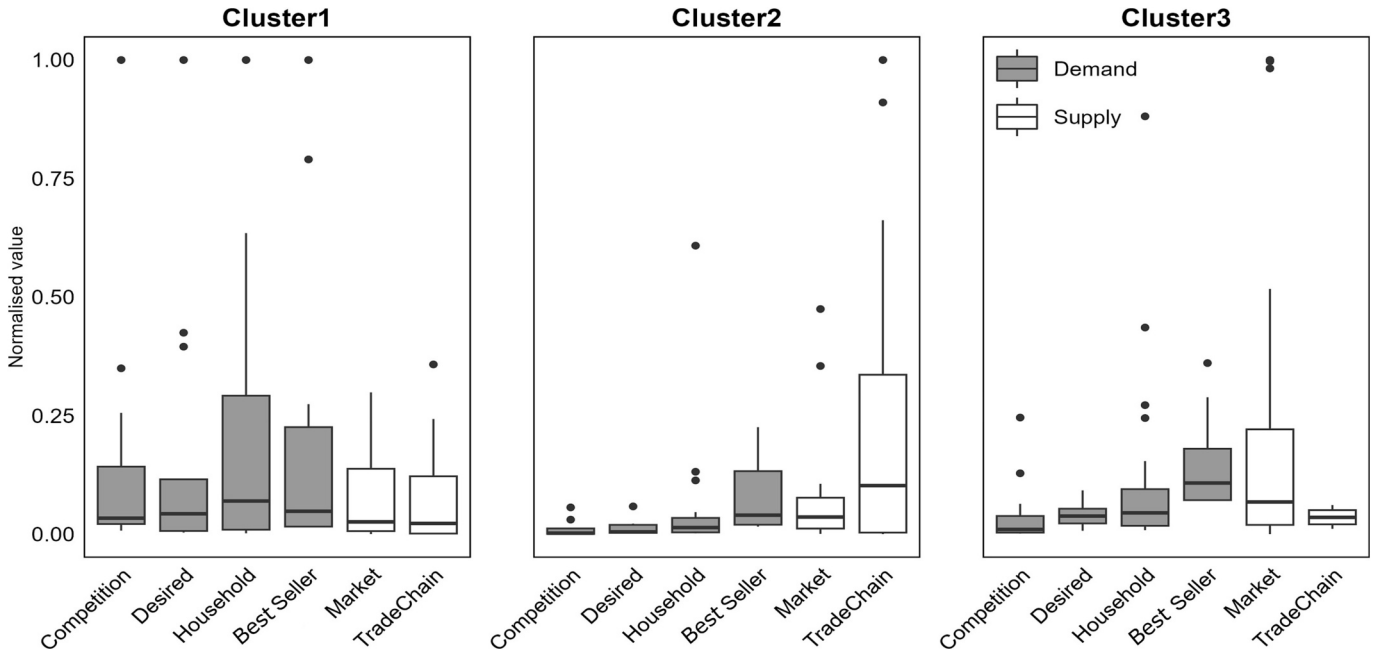
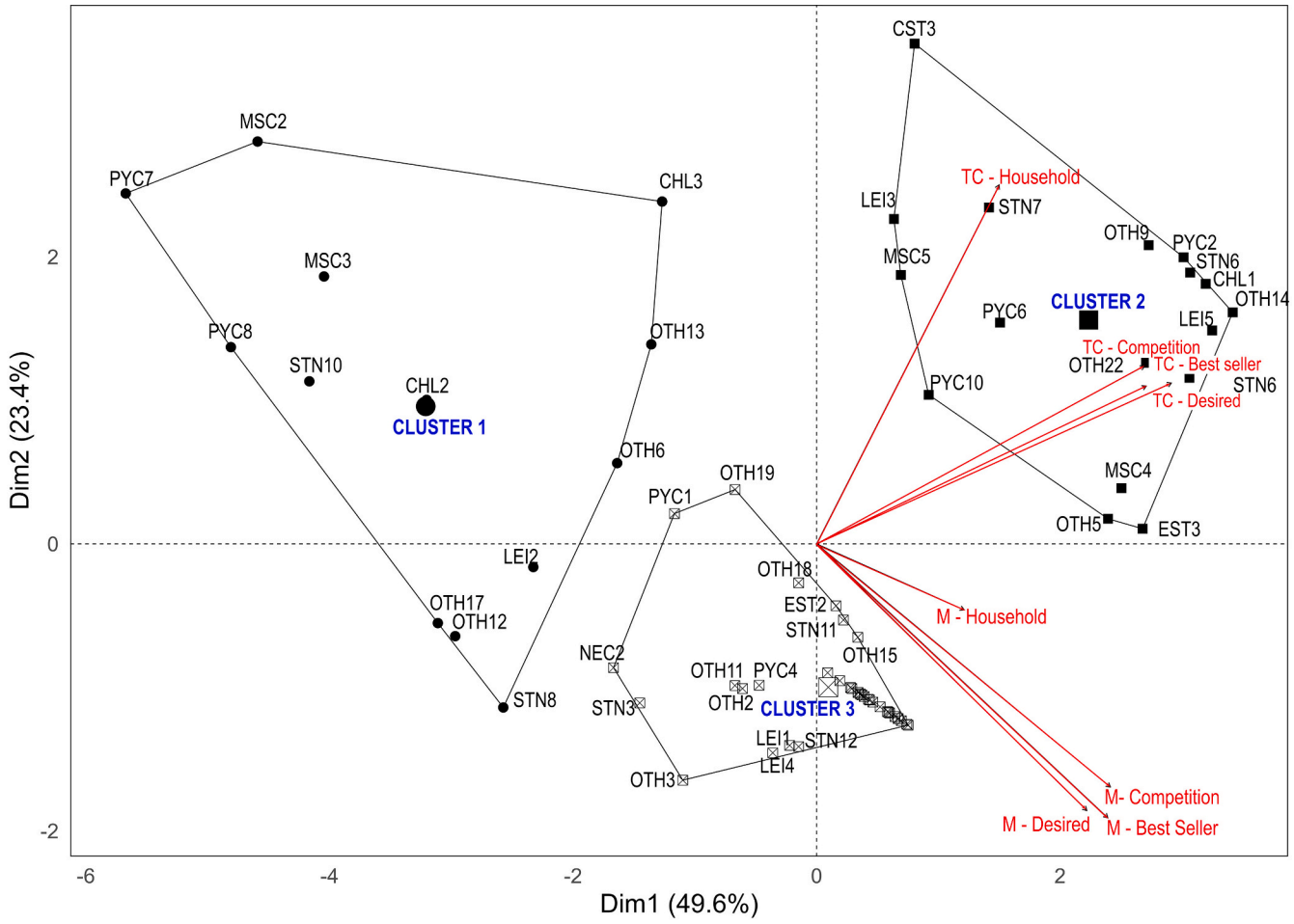


Fig. 1. Boxplot showing the range of normalized value for each supply and demand measure for each of the identified trade interaction clusters.



Abbreviations: TC= Trade chain; M= Market; CHL= Chloropseidae; EST= Estrildidae; LEI= Leiothrichidae; MSC= Muscicapidae; NEC= Nectariniidae; OTH= Other; PYC=Pycnonotidae; STN=Sturnidae

Fig. 2. Principal Component Analysis (PCA) ordination showing the relationship between species and the eight of their supply-demand pairings (or their Trade Interaction Values - TIV). The species are plotted based on their emerging grouping patterns, and points representing clusters are Cluster 1 (circle); Cluster 2 (square); and Cluster 3 (cross-squares). The supply-demand pairings are displayed as vector arrows. Value of the TIV used to plot this PCA can be found in Supplementary Material E.

and small birds being equally significant), followed by species endemicity. Mimicry ability was important, with non-mimics, incidental mimics, and flexible mimics ranked in that order. Population status was also a contributing factor. Interestingly, all family groups except Muscicapidae and Chloropseidae were important for Cluster 3.

3.3. Predicted trade interaction clusters for supply-only (unlabelled) species

There was a higher percentage of species in the supply side predicted belonging to a TIV cluster with medium or high probability (92.3 %) than low probability (7.7 %), indicating potential prominence of a substitution effect. Specifically, more species were predicted with high probability (91 species or 47.2 %) than mid probability (86 species or 44.6 %). Only 7.7 % (or 15 species) had low probability and therefore have higher likelihood of being opportunistically supplied.

Most species (101 species) were predicted to belong to Cluster 3, with 42 species (41.6 %) predicted with mid probability and 59 species (58.4 %) with high probability. This was dominated by families from the 'Other' category (40 % high and 31 % mid), followed by finches (8 % high and 3 % mid), and sunbirds (5 % high and 2 % mid). Cluster 1 had the second highest number (45 species) of predicted species, with 21 species (46.7 %) predicted with mid probability and 24 species (53.3 %) with high probability. The prediction was dominated by families categorised into 'Other' (69 % total with 27 % high probability and 42 % mid probability), followed by starlings (16 %, all high). Cluster 2 had the least predicted species (32 species), with 75 % mid probability and 25 % high. The prediction was dominated by old-world flycatchers (53 %, all mid probability), bulbuls (22 %, all high probability), and starlings (16 % total, 13 % high and 3 % mid). Finally, opportunistic species did not have a consistent trait pattern and were mostly dominated by families from the 'Other' category (53 %) (See supplementary material H for more detailed information).

4. Discussion

We explored analysing data from various sources to identify potential presence of patterns that can serve as a proxy for market dynamics and a source of important information when deciding conservation steps forward. We found that it was possible to group species based on demand and supply patterns (Fig. 2), use species traits to characterise them (Fig. 3), and predict classification of species into these groups.

The first cluster we found were species recorded with high relative demand values, higher than its paired relative market and trade chain supply values (Fig. 2). Families important to this cluster (Muscicapidae, Chloropsidae, Leiothrichicae) were ones popularly used for

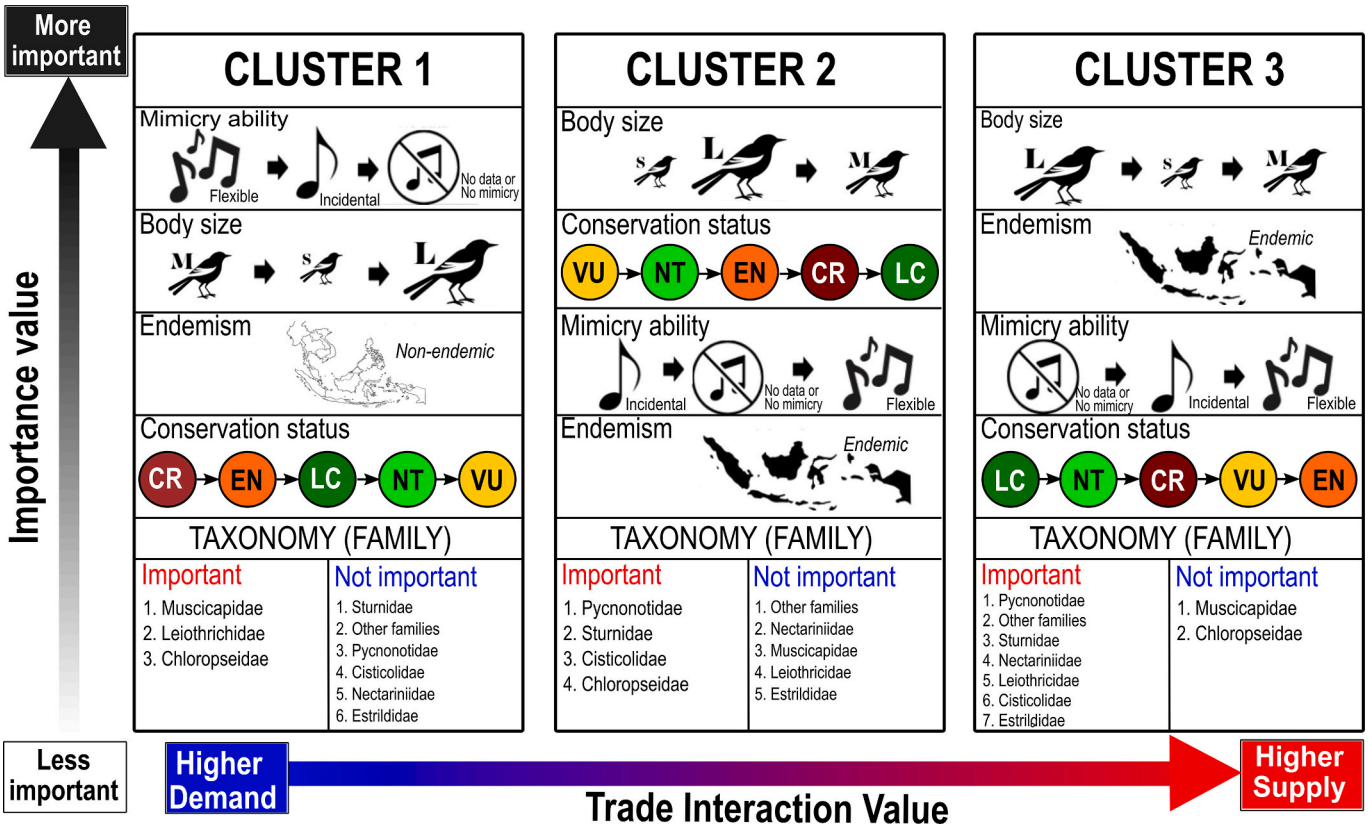


Fig. 3. Illustration of the predictor variables that drive the classification of species into three supply-demand interaction clusters. Arrows show the direction of the layout, with higher importance variables located at the top with variables decreasing in importance lower down. Species with higher demand are on the left and higher supply on the right. Conservation status is based on the Red List (LC = least concern, NT = near threatened, VU = vulnerable, EN = endangered, and CR = critically endangered). Raw importance values of traits can be found in Supplementary Material F.

competitions (Angguni et al., 2020; Armstrong and Chng, 2020; Mirin and Klinck, 2021; Widianto, 2019) and the most important trait (mimicry) is the trait important for winning competitions (Blakey, 2009; Turut, 2012). Unfortunately, this cluster also shows patterns reflecting population decline. This is seen from the conservation status where critically endangered and endangered the most important conservation status characterising this cluster. The preference in size of birds might be reflective of the identity of species of interest in this cluster, the most popular competition birds are those middle sized (Dewanto and Sitanggang, 2009; Turut, 2012).

An interesting finding for Cluster 1 is that endemism is not a trait characterising the cluster, as most species in this cluster and those used in competitions are widely distributed species. Moreover, several competition species are known to already have captive breeding practices present. Therefore, the high demand in this cluster might reflect consumers acquiring birds from these sources and not from markets and trade chains. Unfortunately, we do not have enough information to confirm this trend, yet it warrants closer research into this issue to further understand the potential for captive breeding and best approaches to navigate it to ensure that it does support conservation rather than threaten wild populations (Bulte and Damania, 2005).

Our second cluster was characterised by species with relative demand values higher than relative physical market supply, but lower than relative trade chain confiscations. Moreover, market sellers report that species that belong in this cluster sell quite well (Fig. 1). With the information currently known about the trade, this cluster might not only be the most difficult to understand but also to monitor. The trade of species in this cluster seems to either occur in a very rapid manner (leaving none detected in physical markets) or occur in non-physical markets (being detected in the trade chain in confiscations show evidence of supply) (Wyatt, 2013). Records of relative trade chain supply being higher than other measures indicate presence of illegal wild harvesting practices. More concerningly, the conservation status important for this cluster is vulnerable or near threatened conservation status, indicating potential active decline (Fig. 3).

Body size is another trend difficult to understand. There have been signs of an increase in demand and smuggling of small-bodied species (such as sunbirds and white-eyes) in the trade (Indraswari et al., 2020). This is also followed by emerging small bird competition categories, which may partly describe what this cluster is catering to. However, this does not explain the patterns of large sized birds characterising this cluster at the same level of importance as small birds. Nor does it explain how the mimicry trait characterising this cluster are species with either incidental mimicry or ones with no record or known traits of mimicry. Weaker mimicry traits mean that it may not be used for competitions. Concerningly, there is little known information on captive breeding practices present for species in this cluster. This along with high confiscations indicates that the species in this cluster are more likely wild harvested. We currently do not have enough data to fully grasp what demand this supply is catering to, therefore further research using other approaches is needed and it is needed promptly if we were to prevent further wild population declines.

Cluster 3 exhibited higher household demand compared to the other clusters with large proportion being in the supply side from physical markets. This cluster is characterised by species that show no need for no mimicry ability, preference for more-rarely available endemics, and high diversity of family and species, traits that reflect collection and status-based syndromes, such as the Veblen effect (Leibenstein, 1950) anthropogenic Allee effect (Almeida et al., 2024), or irregular collecting behaviour on-based needs (Mackenzie et al., 2024). All which focus on

social status (Rentschlar et al., 2018). In songbird keeping culture, species for these needs are likely kept as household pets. Having songbird show collective species traits would be concerning because it would mean that when building a collection, any species could be at risk, especially rare, protected, and difficult to acquire species (Cekavicius and Pajarskaite, 2012; Raghavan et al., 2013; Veblen, 2009). Currently, species within this cluster are generally at lower conservation statuses, however this is a pattern that would need more monitoring efforts to ensure it does not threaten wild populations.

Our second objective of exploring patterns is identifying the potential presence of the substitution effect and opportunistic supply. Opportunistic supply seems to be present but are a small proportion of unlabelled species (7.7 %). Opportunistic supply commonly derives from hunting bycatch (Gephart and Pace, 2015) however little information remains on how common these practices are for songbird trade, further warranting a pattern that needs more effort to investigate.

The substitution effect seems more prominently present compared to opportunistic supply. The fact that over 90 % of unlabelled species were classified into existing TIV clusters, as well as the majority of these being classified with high probability further strengthens that theory. The substitution effect is present when sellers would like to increase diversity of goods supplied in the market. Sellers would like to provide goods with similar traits to those already known in demand (i.e.: one of the three market clusters identified previously) to increase likelihood of purchase. Often species in high demand have high price points, therefore the substitution effect would also target consumers that would like a wider choice of goods with similar traits but at lower prices. Providing a diversity of substitutes also allows access to wider consumer markets with varying preferences, capitalising on the effect while differentiating their products and maintaining competitive advantages (Hatfield et al., 2019).

Cluster 3 had both the highest number and proportion of species with a high probability of being in the market as potential substitutes, which aligns with its likely role in fulfilling demand for household pets. This cluster is characterised by a high diversity of species, making it easier for additional species to enter the market and offer buyers a wider range of options. Cluster 1 followed closely, with 53.3 % of its predicted unlabelled species showing a high probability of belonging to it. This is also intuitive, given that Cluster 1 corresponds to the highest demand; it is reasonable to expect the market to prioritise providing substitutes for species in this cluster.

Interestingly, several substitute species are not following taxonomic patterns, showing that traits are more important than species taxonomy. For Cluster 1, the most important trait, mimicry, is not necessarily dependent on taxonomy (Goller and Shizuka, 2018), with the majority of Cluster 1 comprises of various 'Other' family groups. For Cluster 2, there is more consistency of species than other clusters, with Bulbuls having high probability while other families predominantly having mid-probabilities. Unlabelled Old-world flycatchers (Muscicapidae), a family important for Cluster 1 but not for Cluster 2, were prevalent however the flycatchers in this cluster had incidental mimicry and not flexible mimicry important for Cluster 1.

4.1. Using these findings to address future research

As we mentioned in the introduction, our goal here is to identify potential patterns present from data gathered from different sources. We highlight that the patterns here are to be considered as starting points highlighting areas that need to be investigated deeper. We found from these patterns alone, several aspects that are of concern, however, would need more research to confirm before responding to.

We highlight the need to move away from single sided market data (supply or demand) and look deeper into developing modelling and deep analytical approaches that can make sense and combine data (despite scarcity) to identify and make sense of patterns (Kubo et al., 2025), especially newly emerging ones (Shepherd et al., 2024). Our approach found that it is traits and not specifically species identities that drive market demand and supply (Fiennes et al., 2024). We found that mimicry plays an important role in demand, especially since it seems to be the driver for Cluster 1. However, there are several species in Cluster 1, each with different demand levels, and we are yet to know, besides mimicry, what traits drive species-specific demand. Hobbyists are drawn to the melody of the songbird (Mirin and Klinck, 2021) therefore there might be other variables, such as song complexity or song length (Dewanto and Sitanggang, 2009; Turut, 2012) that drives demand. Understanding this aspect, will further support identification of species-specific demand and aid in developing demand reduction strategies.

Looking at single sided data and focused on species would not have found such patterns. Furthermore, we found potential presence of substitution effects significantly higher than opportunistic trade as well as patterns of supply catering to collectors of songbirds. Both patterns which indicate unlimited possibilities of diversity of species entering the trade as there seem to be a high diversity of demand the supply side is aiming to cater to. A second concerning pattern is the presence of high proportion of supply from the trade chain (which is only a significantly small snapshot of what truly occurs) which may be catering to directly to a very little-known pattern of demand through unknown means.

A pattern we found might be key to understand the best conservation solution. Demand of some species in this work might be catered to by captive breeding, decreasing capture of wild individuals. Although this shows potential, more research needs to be done beforehand to ensure any intervention would benefit populations rather than threaten them (Damania and Bulte, 2007; Tensen, 2016).

Our study focused on the trade in Indonesian songbirds, however there are similar patterns and cases of unsustainable trade in other taxa (Barber-Meyer, 2010; Carpenter et al., 2004; Gomez et al., 2023; Nóbrega Alves et al., 2013; Phelps and Webb, 2015). Our analytical tools were designed so they can be replicated elsewhere and for other taxa, and we hope that it would extend to do so. Having market-based information will be critical for informing decision-makers on how to tackle illegal and sustainable markets, help protect wildlife populations, particularly those of threatened species, and direct action to broadening target to species traits and groups of species rather than only targeted ones.

CRediT authorship contribution statement

Karlina Indraswari: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sicily Fiennes:** Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Phillip Cassey:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Ganjar Cahyadi:** Writing – review & editing, Writing – original draft, Validation, Investigation, Data curation. **Richard Noske:** Writing – review & editing. **Fattreza Ihsan:** Writing – review & editing, Data curation. **Connie Susilawati:** Writing – review & editing, Supervision, Conceptualization. **Chris R. Shepherd:** Writing – review & editing. **Duan Biggs:** Writing – review & editing, Supervision. **Clevo Wilson:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During some parts of the revision phase, the authors used the assistance of ChatGPT in some parts of this manuscript to improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

A list of species found in this research and the patterns that emerged from species trade interaction values, and other patterns are available by request to the authors. We intentionally did not disclose identity of species due potential trade threat. Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2025.111318.

Data availability

Data will be made available on request.

References

Almeida, R.J., Hyde, M.C., Lockwood, J.L., 2024. How do we identify anthropogenic Allee effects in the wildlife trade? Conserv. Lett. 17 (6). https://doi.org/10.1111/conl.13070.

Angguni, T., Mulyani, Y.A., Mardiastuti, A., 2020. Bird species contested at songbird competition in Jabodetabek Region, Indonesia. In: IOP Conf. Series: Earth and Environmental Science, p. 762.

Armstrong, O.H., Chng, S.C.L., 2020. Distancing the flock: bird singing competitions fly online to avoid covid-19. TRAFFIC Bulletin 23 (2), 49–55.

Auliya, M., Altherr, S., Ariano-Sanchez, D., Baard, E.H., Brown, C., Brown, R.M., Cantu, J.C., Gentile, G., Gildenhuys, P., Henningheim, E., Hintzmann, J., Kanari, K., Krvavac, M., Lettink, M., Lippert, J., Luiselli, L., Nilson, G., Nguyen, T.Q., Nijman, V., Ziegler, T., 2016. Trade in live reptiles, its impact on wild populations, and the role of the European market. Biol. Conserv. 204, 103–119.

Barber-Meyer, S.M., 2010. Dealing with the clandestine nature of wildlife-trade market surveys. Conservation Biology: The Journal of the Society for Conservation Biology 24 (4), 918–923.

Bergin, D., Chng, S.C.L., Eaton, J.A., Shepherd, C.R., 2017. The final straw? An overview of straw-headed bulbul Pycnonotus zeylanicus trade in Indonesia. Bird Conservation International 1–7.

Blakey, J., 2009. Wild Java in a cage. Geographical 40–45. May 2009.

Blundell, A.G., Mascia, M.B., 2005. Discrepancies in reported levels of international wildlife trade. Conservation Biology: The Journal of the Society for Conservation Biology 19 (6), 2020–2025.

Bulte, E.H., Damania, R., 2005. An economic assessment of wildlife farming and conservation. Conservation Biology: The Journal of the Society for Conservation Biology 19 (4), 1222–1233.

Bush, E.R., Baker, S.E., Macdonald, D.W., 2014. Global trade in exotic pets 2006–2012. Conservation Biology: The Journal of the Society for Conservation Biology 28 (3), 663–676.

Cahyadi, G., 2018. Pasar Burung sebagai "Hotspot" Keanekaragaman Hayati di Perkotaan: Deskripsi Potensi akan Dampaknya terhadap Ekosistem dan Konservasi. Seminar Nasional Perhimpunan Biologi Indonesia.

Carpenter, A.I., Marcus Rowcliffe, J., Watkinson, A.R., 2004. The dynamics of the global trade in chameleons. Biol. Conserv. 120 (2), 291–301.

Cekavicius, T., Pajarskaite, M., 2012. Pets as Status Symbols. https://www.diva-portal.org/smash/record.jsf?pid=diva2:531243.

Challender, D.W.S., Brockington, D., Hinsley, A., Hoffmann, M., Kolby, J.E., Massé, F., Natusch, D.J.D., Oldfield, T.E.E., Outhwaite, W., 't Sas-Rolfes, M., Milner-Gulland, E. J., 2022. Mischaracterizing wildlife trade and its impacts may mislead policy processes. Conserv. Lett. 15 (1). https://doi.org/10.1111/conl.12832.

Charrad, M., Ghazzali, N., Boiteau, V., Niknafs, A., 2014. NbClust: an R package for determining the relevant number of clusters in a data set. J. Stat. Softw. 61, 1–36.

Chng, S.C.L., Eaton, J.A., 2016. In the Market for Extinction: Eastern and Central Java. TRAFFIC South East Asia.

Chng, S.C.L., Eaton, J.A., Krishnasamy, K., Shepherd, C.R., Nijman, V., 2015. In the Market for Extinction: An Inventory of Jakarta's Bird Markets. TRAFFIC South East Asia.

Chng, S.C.L., Guciano, M., Eaton, J.A., 2016. In the market for extinction: Sukahaji, Bandung, Java, Indonesia. BirdingASIA 26, 22–28.

Chng, S.C.L., Krishnasamy, K., Eaton, J.A., 2018a. In the market for extinction: the cage bird trade in Bali. Forktail 34 (September), 35–41.

Chng, S.C.L., Shepherd, C.R., Eaton, J.A., 2018b. In the market for extinction: birds for sale at selected outlets in Sumatra. TRAFFIC Bulletin 30 (1), 15–22.

Chng, S.C.L., Saaban, S., Wechit, A., Krishnasamy, K., 2021. Smuggled for its Song - The Trade in Malaysia's Oriental Magpie-robins. TRAFFIC Southeast Asia.

Damania, R., Bulte, E.H., 2007. The economics of wildlife farming and endangered species conservation. Ecological Economics: The Journal of the International Society for Ecological Economics 62 (3–4), 461–472.

Dewanto, A., Sitanggang, M., 2009. Buku pintar merawat dan melatih burung kicauan. AgroMedia.

Donald, P.F., Fernando, E., Brown, L., Busana, M., Butchart, S.H.M., Chng, S., de la Colina, A., Ferreira, J.M., Jain, A., Jones, V.R., Lapido, R., Malsch, K., McDougall, A., Muccio, C., Nguyen, D., Outhwaite, W., Petrovan, S.O., Stafford, C., Sutherland, W. J., Safford, R., 2024. Assessing the global prevalence of wild birds in trade. Conservation Biology: The Journal of the Society for Conservation Biology 38 (5), e14350.

Eaton, J.A., Shepherd, C.R., Rheindt, F.E., Harris, J.B.C., Van Balen, S.B., Wilcove, D.S., Collar, N.J., 2015. Trade-driven extinctions and near-extinctions of avian taxa in Sundaic Indonesia. Forktail 31, 1–12.

Fiennes, S., Hardianto, N., Ansari, S.D., Dwiyahreni, A.A., Jackson, T., Holmes, G., Birchall, C., Hassall, C., 2024. Rethinking extinction "crises": the case of Asian songbird trade. Cambridge Prisms. Extinction 2, e15.

Fukushima, C.S., Mammola, S., Cardoso, P., 2020. Global wildlife trade permeates the Tree of Life. Biol. Conserv. 247 (July), 71–76.

Gephart, J.A., Pace, M.L., 2015. Structure and evolution of the global seafood trade network. Environ. Res. Lett. 10 (12), 125014.

Goller, M., Shizuka, D., 2018. Evolutionary origins of vocal mimicry in songbirds. Evolution Letters 2 (4), 417–426.

Gomez, L., Joseph, T., Heinrich, S., Wright, B., D'Cruze, N., 2023. Illegal trade of pangolins in India with international trade links: an analysis of seizures from 1991 to 2022. European Journal of Wildlife Research 69 (4). https://doi.org/10.1007/s10344-023-01708-9.

Haryoko, T., 2010. Komposisi Jenis dan Jumlah Burung Liar yang Diperdagangkan di Jawa Barat. Berita Biologi 10 (3), 385–391.

Hatfield, J.W., Kominers, S.D., Nichifor, A., Ostrovsky, M., Westkamp, A., 2019. Full substitutability. Theoretical Economics 14 (4), 1535–1590.

Huber, J., Puto, C., 1983. Market boundaries and product choice: illustrating attraction and substitution effects. J. Consum. Res. 10 (1), 31.

Hughes, L.J., Morton, O., Scheffers, B.R., Edwards, D.P., 2023. The ecological drivers and consequences of wildlife trade. Biol. Rev. Camb. Philos. Soc. 98 (3), 775–791.

Indraswari, K., 2021. A multi-faceted analysis of Indonesia's songbird trade economy: An evidence based market solution (Doctoral dissertation, Queensland University of Technology).

Indraswari, K., Friedman, R.S., Noske, R., Shepherd, C.R., Biggs, D., Susilawati, C., Wilson, C., 2020. It's in the news: characterising Indonesia's wild bird trade network from media-reported seizure incidents. Biol. Conserv. 243. https://doi.org/10.1016/j.biocon.2020.108431.

Iqbal, M., 2015. Looking at online bird trading in Indonesia: a case study from South Sumatra. BirdingASIA 24 (November), 132–135.

Iskandar, B.S., Iskandar, J., Partasasmita, R., 2019. Hobby and business on trading birds: case study in bird market of Sukahaji, Bandung, West Java and Splendid, Malang, East Java (Indonesia). Biodiversitas 20 (5), 1316–1332.

Jaynes, E.T., 2003. Probability Theory: The Logic of Science. Cambridge University Press.

Jepson, P., Ladle, R.J., 2009. Governing bird-keeping in Java and Bali: evidence from a household survey. Oryx: The Journal of the Fauna Preservation Society 43 (3), 364–374.

Juhardiansyah, Erianto, H., Idham, H.M., 2019. Studi jenis burung yang diperdagangkan di kota ketapang. Jurnal Hutan Lestari 7 (1), 237–247.

Kassambara, A., Mundt, F., 2017. Package 'factoextra'. Extract and Visualize the Results of Multivariate Data Analyses 76 (2). https://piyanit.nl/wp-content/uploads/2020/10/factoextra.pdf.

Kubo, T., Mieno, T., Uryu, S., Terada, S., Veríssimo, D., 2025. Banning wildlife trade can boost the unregulated trade of threatened species. Conserv. Lett. 18 (1). https://doi.org/10.1111/conl.13077.

Lê, S., Josse, J., Husson, F., 2008. FactoMineR: an R package for multivariate analysis. J. Stat. Softw. 25, 1–18.

Lee, J., Chng, S.C.L., Eaton, J.A., 2016. Conservation strategy for Southeast Asian songbirds in trade. In: Recommendations from the first Asian Songbird Trade Crisis Summit 2015 held in Jurong Bird Park, Singapore, 27–29 September 2015. Wildlife Reserves Singapore. TRAFFIC Southeast Asia. https://doi.org/10.13140/RG.2.2.12805.96483.

Leibenstein, H., 1950. Bandwagon, snob, and Veblen effects in the theory of consumers' demand. Q. J. Econ. 64 (2), 183–207.

Leupen, B.T.C., Gomez, L., Shepherd, C.R., Nekaris, K.A.-I., Imron, M.A., Nijman, V., 2020. Thirty years of trade data suggests population declines in a once common songbird in Indonesia. European Journal of Wildlife Research 66 (6), 98.
Liaw, A., Wiener, M., 2007. Classification and Regression by randomForest.
Liew, J.H., Kho, Z.Y., Lim, R.B.H., Dingle, C., Bonebrake, T.C., Sung, Y.H., Dudgeon, D., 2021. International socioeconomic inequality drives trade patterns in the global wildlife market. Science Advances 7 (19). https://doi.org/10.1126/sciadv.abf7679.
Lubis, A.S., Zulfan, Chania, M.F., Adha, I.M., Kumalasari, F., 2024. Analysis of the use and application of mathematics in economics: demand and supply functions. Journal of Research in Mathematics Trends and Technology 6 (1), 16–23.
M. Jones, Z., J. Linder, F., 2016. edarf: exploratory data analysis using random forests. Journal of Open Source Software 1 (6), 92.
Mackenzie, S., Yates, D., Hübschle, A., Bērziņa, D., 2024. Irregularly regulated collecting markets: antiquities, fossils, and wildlife. Crime Law Soc. Chang. 82 (5), 1111–1130.
Marshall, H., Collar, N.J., Lees, A.C., Moss, A., Yuda, P., Marsden, S.J., 2020. Characterizing bird-keeping user-groups on Java reveals distinct behaviours, profiles and potential for change. People and Nature 1–12 vember 2019.
Mirin, B.H., Klinck, H., 2021. Bird singing contests: looking back on thirty years of research on a global conservation concern. Global Ecology and Conservation 30, e01812.
Mulyana, T., Erianto, H., Kartikawati, S.M., 2019. Status perlindungan burung liar yang diperdagagnkan di kabupaten Kubu Raya. Jurnal Hutan Lestari 7 (3), 1412–1423.
Nijman, V., Sari, S.L., Siriwat, P., Sigaud, M., Nekaris, A.-I., 2017. Records of four critically endangered songbirds in the markets of Java suggest domestic trade is a major impediment to their conservation. BirdingASIA 27 (August), 20–25.
Nijman, V., Campera, M., Ardiansyah, A., Balestri, M., Bizri, H.R.E., Budiadi, B., Dewi, T., Hedger, K., Hendrik, R., Imron, M.A., Langgeng, A., Morcatty, T.Q., Weldon, A.V., Nekaris, K.A.I., 2021. Large-scale trade in a songbird that is extinct in the wild. Diversity 13 (6), 238.
Nóbrega Alves, R.R., De Farias Lima, J.R., Araujo, H.F.P., 2013. The live bird trade in Brazil and its conservation implications: an overview. Bird Conservation International 23 (1), 53–65.
Nuruliawati, Mardhiah, U., Muktamarianti, A.I., Muttaqin, E., Sheherazade, Surya, S., Nugroho, A., Rahmadi, C., Widiyanto, D., Leggett, M., Mardiah, S., Veríssimo, D., 2024. Using SMS surveys to understand songbird ownership and shark product consumption in Indonesia. Oryx: The Journal of the Fauna Preservation Society 58 (4), 437–447.
Okarda, B., Muchlish, U., Kusumadewi, S.D., Purnomo, H., 2022. Categorizing the songbird market through big data and machine learning in the context of Indonesia's online market. Global Ecology and Conservation 39, e02280.
Olivares-Rojas, J., Cook, C.N., Ward, M.S., Walsh, J.C., 2024. Species and ecological communities as management surrogates for threatened biodiversity. Biodivers. Conserv. 33 (3), 987–1008.
Oyanedel, R., Gelcich, S., Mathieu, E., Milner-Gulland, E.J., 2022. A dynamic simulation model to support reduction in illegal trade within legal wildlife markets. Conservation Biology: The Journal of the Society for Conservation Biology 36 (2), e13814.
Pantić, N., Cvijanović, D., Imamović, N., 2021. Economic analysis of the factors influencing the supply and demand of raspberry. Ekonomika Poljoprivrede 68 (4), 1077–1087.
Patel, N.G., Rorres, C., Joly, D.O., Brownstein, J.S., Boston, R., Levy, M.Z., Smith, G., 2015. Quantitative methods of identifying the key nodes in the illegal wildlife trade network. Proc. Natl. Acad. Sci. 112 (26), 7948–7953.
Phelps, J., Webb, E.L., 2015. "Invisible" wildlife trades: Southeast Asia's undocumented illegal trade in wild ornamental plants. Biol. Conserv. 186, 296–305.
R Core Team, 2024. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. https://www.R-project.org/.
Raghavan, R., Dahanukar, N., Tlusty, M.F., Rhyne, A.L., Krishna Kumar, K., Molur, S., Rosser, A.M., 2013. Uncovering an obscure trade: threatened freshwater fishes and the aquarium pet markets. Biol. Conserv. 164, 158–169.
Rentschlar, K.A., Miller, A.E., Lauck, K.S., Rodiansyah, M., Bobby, Muflihati, Kartikawati., 2018. A silent morning: the songbird trade in Kalimantan, Indonesia. Tropical Conservation Science 11, 1–10.
Rheindt, F.E., Baveja, P., 2019. The extinction-in-progress in the wild of the Barusan Shama Copsychus (malabaricus) melanurus. Forktail 35, 30–37.
Santoso, B., 2021. Budidaya dan Memaster Kolibri Siap Menjadi Jawara Kontes. Pustaka Baru Press.
Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. J. Financ. 19 (3), 425–442.
Shepherd, C.R., Chng, S., 2017. Second Southeast Asian songbird crisis summit. TRAFFIC Bulletin 29 (1), 3–4.
Shepherd, C.R., Nijman, V., Nelson, S.S., Leupen, B.T.C., Bruslund, S., 2024. A newly emerging trade in New Guinea's butcherbirds (Cracticinae) in Indonesia. Eur. J. Wildl. Res. 70 (4). https://doi.org/10.1007/s10344-024-01816-0.
Siriwat, P., Nijman, V., 2018. Using online media-sourced seizure data to assess the illegal wildlife trade in Siamese rosewood. Environ. Conserv. 45 (4), 419–424.
Tensen, L., 2016. Under what circumstances can wildlife farming benefit species conservation? Global Ecology and Conservation 6, 286–298.
Tittensor, D.P., Harfoot, M., McLardy, C., Britten, G.L., Kecse-Nagy, K., Landry, B., Outhwaite, W., Price, B., Sinovas, P., Blanc, J., Burgess, N.D., Malsch, K., 2020. Evaluating the relationships between the legal and illegal international wildlife trades. Conserv. Lett. 13 (5). https://doi.org/10.1111/conl.12724.
Toomes, A., García-Díaz, P., Stringham, O.C., Ross, J.V., Mitchell, L., Cassey, P., 2022. Drivers of the Australian native pet trade: the role of species traits, socioeconomic attributes and regulatory systems. J. Appl. Ecol. 59 (5), 1268–1278.
Turut, R., 2012. Burung Ocehan Juara Kontes. Penebar Swadaya Grup.
Van Uhm, D.P., Moreto, W.D., 2018. Corruption within the illegal wildlife trade: a symbiotic and antithetical enterprise. The British Journal of Criminology 58 (4), 864–885.
Veblen, T., 2009. The Theory of the Leisure Class. The Floating Press.
Widianto, A., 2019. Budi daya segala jenis burung kicauan. laksana.
Wyatt, T., 2013. Wildlife Trafficking a Deconstruction of the Crime, the Victims, and the Offenders. Springer.