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Aaron M. Anderson
USDA/APHIS/WS National Wildlife Research Center, aaron.m.anderson@aphis.usda.gov

David S. Carpenter
US Department of Agriculture, Animal and Plant Health Inspection Service, Wildlife Services, National Wildlife Research Center

Michael J. Begier
US Department of Agriculture, Animal and Plant Health Inspection Service, Wildlife Services

Bradley F. Blackwell
USDA/APHIS/WS National Wildlife Research Center, bradley.f.blackwell@aphis.usda.gov

Travis L. DeVault
USDA/APHIS/WS National Wildlife Research Center, Travis.L.DeVault@aphis.usda.gov

See next page for additional authors

Authors
Aaron M. Anderson, David S. Carpenter, Michael J. Begier, Bradley F. Blackwell, Travis L. DeVault, and Stephanie A. Shwiff

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Modeling the cost of bird strikes to US civil aircraft

Aaron Anderson [a,*], David S. Carpenter [a], Michael J. Begier [b], Bradley F. Blackwell [c], Travis L. DeVault [c], Stephanie A. Shwiff [a]

[a] US Department of Agriculture, Animal and Plant Health Inspection Service, Wildlife Services, National Wildlife Research Center, United States
[b] US Department of Agriculture, Animal and Plant Health Inspection Service, Wildlife Services, United States
[c] US Department of Agriculture, Animal and Plant Health Inspection Service, Wildlife Services, National Wildlife Research Center, Ohio Field Station, United States

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ABSTRACT

The objective of our analysis is to develop a model of damage costs that arise from collisions between aircraft and birds, based on data drawn from the Federal Aviation Administration National Wildlife Strike Database (NWSD). We develop a two-part model, composed of two separate statistical models, that accounts for the effects of aircraft mass category, engine type, component of the aircraft struck, and the size and number of birds struck. Our results indicate the size of bird, number of birds, and engine ingestions are the largest determinants of strike-related costs. More generally, our result is a model that provides a better understanding of the determinants of damage costs and that can be used to interpolate the substantial amount of missing data on damage costs that currently exists within the NWSD. A more complete accounting of damage costs will allow a better understanding of how damage costs vary geographically and temporally and, thus, enable more efficient allocation of management resources across airports and seasons.

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Introduction

Costs associated with bird–aircraft collisions affect commerce and safety and are widely acknowledged by the aviation community (Blackwell et al., 2009; Dolbeer, 2013). The annual direct costs (aircraft repair costs) associated with bird strikes in the US have been estimated at US$155 million (Dolbeer et al., 2013). This number, however, is likely a substantial underestimate of the magnitude of the problem. A number studies have indicated substantial underreporting of strikes. Dolbeer (2009) estimated that reporting rates at larger airports may approach 40%, and several other studies have suggested reporting rates of less than 20% (Cleary and Dolbeer, 2005; Wright and Dolbeer, 2005). Thus, the true cost of bird strikes in the US is likely substantially higher, especially if indirect costs (e.g. aircraft downtime) are considered. Globally, conservative estimates of the total monetary costs of bird strikes range from US$1.21 to US$1.36 billion annually (Allan and Orosz, 2001). The recognition of the high cost of strikes has led authorities in many developed countries to impose some form of wildlife management requirement on commercial airports (Dolbeer and Wright, 2009; DeVault et al., 2013). Wildlife hazard management regulations in the US (14 Code of Federal Regulations part 139) focus largely on addressing and mitigating wildlife hazards immediately upon detection, regulating land use on or around airports, and conducting wildlife hazard assessments (Cleary and Dolbeer, 2005; FAA, 2007; Blackwell et al., 2009; Dolbeer and Wright, 2009).

* Corresponding author at: 4101 LaPorte Avenue, Fort Collins, CO 80521, United States. Tel.: +1 (970) 266 6264.
E-mail address: Aaron.M.Anderson@aphis.usda.gov (A. Anderson).

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A number of previous studies have analyzed the risks posed by different bird species. Zakrajsek and Bisonette (2005), for example, report that vultures, geese and pelicans are the most hazardous birds to US Air Force aircraft. Dolbeer et al. (2000) presents similar findings and conclude that a better understanding of species-specific risk can guide the allocation of management resources at airports. However, efficient allocation of management resources to mitigate the risk and cost of bird strikes also requires assigning management resources to the airports where the problem is relatively severe. Thus, an accurate understanding of how strike costs vary by airport and over time is beneficial. Unfortunately, fully understanding the geographic and temporal variation in costs is difficult because many reported strikes do not provide cost information. Dolbeer et al. (2013), for example, found that only 16% of reported strikes that indicated an adverse effect reported a damage cost. The estimate of $155 million in annual direct costs accounted for underreporting of damage costs by assuming that reported damage costs were representative of reported strikes that failed to report an estimate of damage costs. While this is a reasonable procedure for estimating damages at a national level, important differences might be missed if applied at an airport level. If the underreporting of costs varies by airport, then assigning a mean damage cost to missing data points is problematic. Some airports will suffer damage costs that are above or below average due to the type and number of aircraft and birds present. Thus, a method of assigning damage costs to strike reports that accounts for the characteristics of the particular strike would be beneficial.

To this end, our objective is to develop a model of damage costs, based on data drawn from the Federal Aviation Administration National Wildlife Strike Database (NWSD). In future analyses, our model will allow estimation and interpolation of strike costs based on certain other characteristics of the strike that have been reported. In addition to its use as an interpolation tool, the model allows the contribution of specific strike characteristics to the cost of the strike to be examined and quantified. In particular, we hypothesize that phase of flight (affecting airspeed and altitude of encounters with birds), aircraft mass, engine type, and component struck would be relevant explanatory variables in a model of strike-related costs.

Our results will be useful for two reasons. First, its use to interpolate missing cost data in the NWSD will provide for a better understanding of how costs vary across airports and over time. This will enable managers to more accurately target airports and seasons with the highest damage costs. Furthermore, it provides a better understanding of the relative contributions of different strike characteristics to the cost of the strike. Such findings are important to understand how vulnerability to strikes varies across aircraft designs and how damage to specific components contributes to costs. The manuscript proceeds by discussing the NWSD and the particular variables that were used in our analysis. Details of the statistical models and estimation procedures are then presented before a detailed discussion of the results. Finally, we offer some concluding remarks regarding the limitations of our analysis and implications of our findings.

Materials and methods

Data

At the time of download, the NWSD included 145,846 reported wildlife strikes from 1990 through 2013. The NWSD reflects only the voluntary reports of wildlife strikes to the FAA from airlines, airports, pilots, and other sources (http://wildlife.faa.gov/). Detailed descriptive statistics regarding the broad dataset are published annually and are publicly available (Dolbeer et al., 2013). The full NWSD contains information on over 90 different variables associated with each strike. Two types of costs are reported in the NWSD: strike-related damage costs and other indirect costs (e.g. flight schedule disruptions, aircraft downtime). However, the indirect costs are reported far less frequently in the NWSD and less is known about the comprehensiveness of existing reports of the indirect costs. Therefore, our focus is limited to modeling direct, strike-related damage costs. It should be noted, however, that some of the reported strike-related damage costs are likely underestimated because they are sometimes reported before the aircraft has been fully evaluated (Dolbeer et al., 2013).

Of the remaining variables in the NWSD, only a subset was appropriate for our analysis. We hypothesize that phase of flight, aircraft mass, engine type, and component struck would be determinants of strike-related costs. We also include measures for the size and numbers of birds involved in a strike. Our research efforts are focused on wildlife strikes between civil and/or commercial aircraft and birds; our analysis excludes strikes with military aircraft and any collision between an aircraft and non-bird wildlife. We focus our attention on those variables which were related to the expected value of damages given that a strike has occurred, and omitted all those variables which are related predominantly to the probability of a strike occurring (e.g. season of year, time of day, geographic region, etc.).[1]

There are also data series that suffer the dual problems of high correlation with other relevant explanatory variables, as well as substantial numbers of missing observations across the NWSD. For example, height and speed are two data series that are relevant, but both are highly correlated with the phase of flight during which the strike occurred. Including both the phase of flight categories as well as the combination of the available height and speed variables would introduce considerable difficulties with inference. In addition, there are tens of thousands of observations for which height and/or speed are unreported, and including these variables in the model would substantially reduce our sample size. In each case where discretion is required regarding including a variable, we opt for the specification which offers the largest possible sample size

[1] It is true that strike costs vary according to region, season, and time. However, costs vary in response to these because the types of birds and aircraft involved in strikes tend to vary by them. Thus, it is preferable to focus on the proximate causes of the variation rather than the indirect causes.

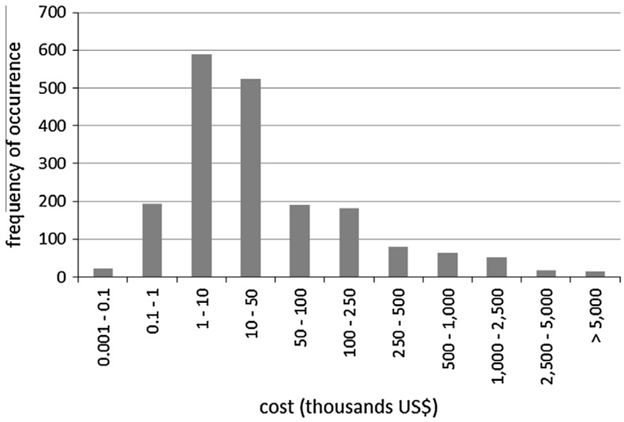

Fig. 1. Distribution of 1928 non-zero costs.

of observations with complete information. Given the suspected multicollinearity issues within the reported variables, estimating our model with the largest available sample size and most parsimonious set of variables seems to be an appropriate strategy for addressing any remaining multicollinearity (Greene, 2003).

It should also be noted that not all strike reports contain sufficiently complete information to include in our sample. Over 90% of the reported strikes in the raw database do not include a direct repair cost. For some of these observations, another available data series indicates whether the strike resulted in no damage. We therefore assume a $0 direct repair cost for those observations. However, there are also observations which indicate by categorical variable that some damage resulted from the bird strike, but provide no explicit report of the cost of that damage. As we cannot interpolate a repair cost from these strike reports, we exclude all such observations, as well as any observation for which the entry was incomplete across our included variables. For example, due to incomplete information across strike reports, observations involving gliders, turboshaft engines for helicopters, and mixed-engine aircraft are absent from our sample. Thus, our analysis is applicable to strikes involving the following forms of propulsion: (1) traditional gas turbine jet engines using exhaust for thrust (turbojets); (2) gas turbine jet engines powering a ducted fan for thrust (turbofans); (3) gas turbine jet engines powering a propeller for thrust (turboprops); and (4) reciprocating piston engines powering a propeller for thrust. After all such exclusions, the sample consists of 60,289 records, 1928 of which involve a non-zero dollar repair cost. The mean cost is US$7,219. Of the non-zero costs, the mean is US$225,739 and the maximum is just over US$40 million (Fig. 1).

Strikes to nearly any part of an aircraft can cause damage and necessitate expensive inspection or repair procedures. However, anecdotal evidence suggests that ingesting birds into one or more engines is a major determinant of the extent of damage and probability of a catastrophic outcome. As such, a set of categorical interaction terms is created, denoting for a given observation whether one engine or multiple engines were struck, and whether or not a bird was ingested by at least one of the struck engines. Note that ingestion is a concern regardless of engine type. While such events are rarer with propeller based propulsion systems, engine ingestion still occurs with reciprocating or turboprop aircraft and a number of these events appear in our sample.

The variables we include are organized into sets of categorical variables indicating different potential determinants of the damage cost resulting from a bird strike. These groupings include the size and number of birds struck, phase of flight during which the strike occurred (parked aircraft, taxiing, take-off runs, climb out, en route to destination, descent, final approach to destination, and landing roll), mass category and engine type of the aircraft involved, the component(s) struck on the aircraft, and whether or not the strike involved ingestion into an engine (Table 1).

Table 1
Variables used in the analysis with counts in parentheses.

Mass category	*Engine type*	*Phase of flight*	*Components struck*
<2250 kg (3014)	Turbofan (51031)	Approach (26466)	Radome (10326)
2251–5700 kg (2765)	Turbojet (3403)	Climb (10250)	Windshield (13878)
5701–27,000 kg (12387)	Reciprocating (136)	Descent (2156)	Nose (11765)
27,001–272,000 kg (41668)	Turboprop (5719)	En route (859)	Propeller (1578)
>272,000 kg (455)		Landing roll (10441)	Wing (7094)
	Birds struck	Take-off run (9920)	Fuselage (9826)
Ingestion	1 (50820)	Parked (28)	Landing gear (3142)
Ingested – 1 Engine (2594)	2–10 (8900)	Taxi (169)	Tail (616)
Ingested – >1 Engine (186)	11–100 (550)		Lights (216)
Not injest. – 1 Engine (3050)	>100 (19)	*Size of birds*	Other (3871)
Not injest. – >1 Engine (144)		Small (34688)	Unknown (5032)
		Medium (22292)	
		Large (3309)	

Models

Our two-part model contains two separate statistical models. The cost data we relied on contains a large number of zeroes, but there are also a substantial number of non-zero damage costs. This type of data would be a natural application of a tobit model for censored data, but for this application it was important to allow variables to have different effects on the probability of a non-zero damage cost and the magnitude of the damage cost (McDonald and Moffitt, 1980). For example, we expect that a bird strike to a light would likely break or destroy the light, such that we have a greatly increased likelihood of observing some positive cost as a result. However, the non-zero repair costs associated with replacing the damaged light would be relatively small. Since a tobit model does not allow this type of flexibility, we model the two processes separately.

Specifically, we apply a binary-choice, heteroskedastic probit model to estimate the probability of a strike generating a non-zero repair cost. As a dependent variable, this model relies on a data series we construct that is zero when cost is zero and a one when the reported cost is non-zero. Separately, we employ a log-linear model to estimate the cost of a strike conditioned on the occurrence of a non-zero repair cost. Thus, the log-linear model only includes those observations that report a non-zero cost. Note that we are somewhat limited in terms of functional form choices because of the categorical nature of our variables. As a result, investigating the use of quadratic terms or logarithmic transformations is not possible. The only plausible alternative in the binary-choice model is to use a logit specification, but binary-choice probit and logit models provide very similar results. For modeling the magnitude of the costs, we choose a log-linear model rather than a linear model because such a specification avoids the problem of negative values for predicted damage costs and provides a substantially better fit.

All variables included in both of our models are categorical, such that excluding one variable within each category to serve as a reference group is necessary to correctly estimate the model.[2] The reference variables within each category are (1) aircraft mass less than 2250 kg, (2) turbofan type engines, (3) large birds (defined subjectively by the strike reporter, relative to “medium” or “small” birds), (4) no engines struck with no ingestion, and (5) one bird struck. No category is omitted within the “components struck” group; unlike the other groups which contain mutually exclusive categories, each of the components is its own independent categorical variable relative to the alternative “this component was not struck”.

A homoskedastic probit model is described mathematically by stating the likelihood of observing a non-zero cost of repairs conditioned on the available empirical data as

$$Prob(Cost_i > 0|\boldsymbol{x}_i) = \Phi(\boldsymbol{x}_i'\boldsymbol{\beta}), \tag{1}$$

where $\boldsymbol{x}_i$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution, which has a constant variance of one. However, estimation of a homoskedastic model in the presence of non-constant variance across observations results in biased and inconsistent parameter estimates.[3] To allow for heteroskedasticity in our model, we use a common specification of $\sigma_i^2 = [\exp(\boldsymbol{z}_i'\gamma)]^2$, where $\boldsymbol{z}_i$ is a vector of explanatory variables (which may contain some or all of the variables in $\boldsymbol{x}_i$), and γ is a vector of parameters to be estimated (Greene, 2003).

Therefore, under the heteroskedastic probit model, the probability of observing a non-zero repair cost for a particular strike is given by

$$Prob(Cost_i > 0|\boldsymbol{x}_i, \boldsymbol{z}_i) = \Phi\left(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\exp(\boldsymbol{z}_i'\gamma)}\right). \tag{2}$$

The likelihood function for this model is

$$L(\boldsymbol{\beta}) = \prod_{i=1}^{60289}\left[\Phi\left(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\exp(\boldsymbol{z}_i'\gamma)}\right)\right]^{(y_i)}\left[1-\Phi\left(\frac{\boldsymbol{x}_i'\boldsymbol{\beta}}{\exp(\boldsymbol{z}_i'\gamma)}\right)\right]^{(1-y_i)}, \tag{3}$$

where $y_i = 1$ if $Cost_i > 0$ and $y_i = 0$ if $Cost_i = 0$. With the parameter estimates $\hat{\boldsymbol{\beta}}$ and $\hat{\gamma}$ in hand, the estimated probability of a damaging strike is given by $\Phi\left(\frac{\boldsymbol{x}_i'\hat{\beta}}{exp(\boldsymbol{z}_i'\hat{\gamma})}\right)$.

In constructing the specification for the heteroskedastic variance term, we want to include as much relevant information as possible in the $\boldsymbol{z}$ vector. As a first attempt, we estimate the model using the full $\boldsymbol{x}$ vector of explanatory variables for both the probability and variance portions of the model (i.e. $\boldsymbol{x} = \boldsymbol{z}$). Beginning with the entire set of explanatory variables is a reasonable starting point because the source of non-constant variance was unknown. Thus, it is desirable to include all variables in the variance model to capture all potential sources of variation. However, this specification fails to achieve convergence using any common method. We then opt to build $\boldsymbol{z}$ category by category. We start from an initial assumption of homoskedasticity, and proceed to add broad categorical groupings to the variance vector one at a time, confirming in each case that the

[2] We also investigated the inclusion of the year the strike occurred, but the associated coefficient was near zero and insignificant in all cases.

[3] As an example of a source of non-constant variance, consider a strike to a light. There little variation in the outcome because damage is very likely and its cost is usually limited. Alternatively, consider a strike to an engine. It could cause no damage, or it could destroy the aircraft. This implies there will be much more variation in some types of observations.

specification converged. Ultimately, this process leads us to include the following categories in: mass category, engine type, size and number of birds, and aircraft component(s) struck into the final specification for the variance term.

The other component of our two-part model is a log-linear model used to predict the repair costs resulting from a strike, given that the strike generated a non-zero repair cost. The model is described by $\ln(y_i) = \boldsymbol{x}_i'\boldsymbol{\alpha} + \upsilon_i$, where $\boldsymbol{x}_i$ is the same vector of explanatory variables as in the probit model, $\boldsymbol{\alpha}$ is a vector of parameters to be estimated, and υ is a zero-mean, normally distributed disturbance term. Note that by specifying both the probit model and log-linear model with same sets of explanatory variables, we are assuming that factors that affect the probability of damage occurring also affect the magnitude of damage. For example, we believe that the size and number of birds struck would affect both the likelihood of damage and its magnitude.

In order for the log-linear model to account for the heteroskedasticity present in the data, we estimate the standard errors of the parameters using White's correction (White, 1980). After obtaining estimates of the parameters, the expected cost of a strike with a non-zero strike cost is given by $\exp(\boldsymbol{x}_i'\hat{\boldsymbol{\alpha}})$. Finally, the expected cost of strike conditioned only on $\mathbf{x}_i$ and $\boldsymbol{z}_i$ is given by

$$\mathrm{E}[Cost_i|\mathbf{x}_i, \boldsymbol{z}_i] = \mathrm{Prob}(Cost_i > 0|\mathbf{x}_i, \boldsymbol{z}_i) * \mathrm{E}[Cost_i|Cost_i > 0, \mathbf{x}_i] = \Phi\left(\frac{\boldsymbol{x}_i'\hat{\boldsymbol{\beta}}}{exp(\boldsymbol{z}_i'\hat{\boldsymbol{\gamma}})}\right) * \exp(\boldsymbol{x}_i'\hat{\boldsymbol{\alpha}}). \tag{4}$$

Although the coefficients of the log-linear model can be interpreted as the partial effect of each variable on $\mathrm{E}[\log(Cost_i)|Cost_i > 0]$, none of the coefficient estimates are directly interpretable in terms of each variable's marginal impact on $\mathrm{E}[Cost_i]$ because $\mathrm{E}[Cost_i]$ is a nonlinear function of the variables. Calculation of the more useful average partial effects of each variable on the expected cost of a strike requires several steps. To calculate the average partial effect of a particular variable x_j, two $\boldsymbol{x}$ vectors were constructed. The first ($\boldsymbol{x}_0$) contains a zero for x_{0j}, zeros for all variables in the same category as x_j, and the sample mean of each variable not in the same category as x_j. The second vector ($\boldsymbol{x}_1$) only differs in that $x_{1j} = 1$. After constructing $\boldsymbol{z}_0$ and $\boldsymbol{z}_1$ in an identical manner, the average partial effect of x_j on the expected cost of a strike is calculated as

$$\text{Average Partial Effect}_\mathrm{j} = \Phi\left(\frac{\boldsymbol{x}_{1j}'\hat{\boldsymbol{\beta}}}{exp(\boldsymbol{z}_{1j}'\hat{\boldsymbol{\gamma}})}\right) * \exp\left(\boldsymbol{x}_{1j}'\hat{\boldsymbol{\alpha}}\right) - \Phi\left(\frac{\boldsymbol{x}_{0j}'\hat{\boldsymbol{\beta}}}{exp(\boldsymbol{z}_{0j}'\hat{\boldsymbol{\gamma}})}\right) * \exp(\boldsymbol{x}_{0j}'\hat{\boldsymbol{\alpha}}). \tag{5}$$

Note that each of the large terms $[\Phi(\cdot) * \exp(\cdot)]$ in Eq. (5) return the expected cost of a strike since $\Phi(\cdot)$ is the probability of a non-zero cost and exp (·) is the expected cost of a strike conditional on it being non-zero. Thus, the first of the large terms in Eq. (5) returns the expected cost of a strike when some particular characteristic of the strike is true (e.g. strike to engine), while the second large term returns the expected cost of strike when that characteristic is not present (e.g. no strike to engine). The difference between these two values is then interpreted as the contribution of that particular strike characteristic or variable to the expected cost.

Results

Estimation results

Convergence is achieved for the probit model after 15 iterations of Newton's method; the likelihood ratio test against a null hypothesis of homoskedasticity has a p-value near zero, confirming the appropriateness of estimating a heteroskedastic model for this sample. The log-linear model fits the data well, generating an adjusted R-squared value of 0.9687. Coefficient estimates along with standard errors are reported in Table 2.

Average partial effects

Average partial effects represent the expected change in costs associated with a strike involving a particular variable, relative to a strike involving the excluded variable for each category (Table 3). For example, the entry of 19.64 for mass category 2251–5700 kg is interpreted as the increase in repair costs we would expect to see relative to the costs of an identical strike to an aircraft less than 2250 kg, while the negative values observed for all aircraft larger than 5701 kg represent reductions in expected costs relative to that same reference group of excluded aircraft.

Discussion

Mass category

With respect to the mass of an aircraft, the excluded category is the lightest category of the sampled aircraft (less than 2250 kg). Our results imply that, all else equal, heavier aircraft tend to sustain smaller repair costs from a damaging strike than do smaller aircraft (Table 3). There are several possible explanations for this estimated outcome. There may be

Table 2
Coefficient estimates from probit model and log-linear model

	Probit Estimate (S.E.)	Variance Estimate (S.E.)	Log-linear Estimate (S.E.)
Intercept	−0.581*** (0.092)	–	9.512*** (0.213)
Mass category			
<2250 kg	reference (–)	reference (–)	reference (–)
2251–5700 kg	0.148· (0.079)	−0.101 (0.072)	0.174 (0.15)
5701–27,000 kg	−0.636*** (0.151)	0.03 (0.084)	0.179 (0.18)
27,001–272,000 kg	−1.625*** (0.236)	0.199* (0.086)	0.142 (0.19)
>272,000 kg	−0.852** (0.268)	0.15 (0.152)	0.368 (0.315)
Engine type			
Turbofan	Reference (–)	Reference (–)	Reference (–)
Reciprocating	0.181· (0.097)	−0.121 (0.081)	−1.614*** (0.181)
Turbojet	0.74*** (0.197)	−0.253 (0.189)	−0.342 (0.366)
Turboprop	−0.073 (0.097)	−0.01 (0.057)	−0.66*** (0.153)
Phase of flight			
Approach	Reference (–)	–	Reference (–)
Climb	0.305*** (0.048)	–	0.337** (0.104)
Descent	0.474*** (0.079)	–	0.48** (0.166)
En route	0.791*** (0.099)	–	0.395** (0.147)
Landing roll	−0.582*** (0.079)	–	−0.035 (0.192)
Take-off run	−0.092 (0.051)	–	0.289* (0.138)
Parked	−0.436 (0.633)	–	−1.588*** (0.186)
Taxi	−0.664· (0.346)	–	−0.124 (1.042)
Bird size			
Small	−1.912*** (0.202)	0.109* (0.051)	−1.275*** (0.121)
Medium	−0.986*** (0.114)	0.035 (0.044)	−0.694*** (0.091)
Large	Reference (–)	Reference (–)	Reference (–)

	Probit Estimate (S.E.)	Variance Estimate (S.E.)	Log-linear Estimate (S.E.)
Components struck			
Radome	0.3** (0.102)	0.08 (0.044)	0.452*** (0.13)
Windshield	0.075 (0.072)	−0.163*** (0.039)	0.128 (0.126)
Nose	−0.036 (0.081)	−0.016 (0.039)	−0.454*** (0.133)
Propeller	−0.319** (0.106)	0.092 (0.072)	−0.035 (0.183)
Wing	0.607*** (0.073)	0.024 (0.037)	0.225* (0.102)
Fuselage	−0.019 (0.081)	−0.086* (0.042)	0.184 (0.139)
Landing gear	−0.199· (0.11)	0.133* (0.055)	−0.394** (0.15)
Tail	0.385** (0.12)	0.273*** (0.083)	0.376** (0.144)
Lights	1.782*** (0.292)	0.812*** (0.17)	−0.908*** (0.207)
Other	0.331*** (0.095)	0.095* (0.048)	−0.236 (0.151)
Unknown	−1.489* (0.637)	0.017 (0.209)	0.21 (0.868)
Engine strikes & ingestion			
Ingested – 1 engine	1.805*** (0.166)	–	2.112*** (0.126)
Ingested – >1 engine	1.9*** (0.233)	–	2.565*** (0.35)
Not ingest. 1 engine	0.428*** (0.07)	–	0.51** (0.167)
Not ingest. >1 engine	0.258 (0.249)	–	0.564 (0.86)
# of birds struck			
1	reference (–)	reference (–)	reference (–)
2–10	0.209** (0.072)	−0.009 (0.037)	0.535*** (0.115)
11–100	0.413· (0.224)	0.008 (0.122)	0.772* (0.357)
>100	0.257 (1.02)	0.251 (0.596)	2.235* (1.095)

Note: ***indicates significance at the .1% level, **at 1%, *at 5%, and · at 10%.

differences in aircraft design and structure or type and placement of engines, which are particular to aircraft of a certain purpose and therefore size, which would then be highly correlated with aircraft mass.

As such, it may be the case that our mass category grouping is capturing fundamental differences between aircraft of different types, and therefore sizes. In addition, it is possible that smaller aircraft may simply be more prone to catastrophic failures stemming from a strike; of the 24 strikes in our sample resulting in destroyed aircraft, 20 of these involved smaller planes from mass categories 1 and 2.

Engine type

Results suggest that there are modest reductions in expected repair costs associated with any of the included engine types relative to the repair costs associated with turbofan engines. Turbofans appear to be the most costly of the engine types to inspect and repair after a cost, and turbojets the least costly (Table 3). Also, reciprocating and turboprop engines tend to be less mechanically prone to experience catastrophic engine damage from a bird strike, due to the smaller air inlets and engine

Table 3
Average partial effects: estimated changes in repair costs.

	Partial Effect		Partial Effect
Mass category		*Components struck*	
Intercept	–	Radome	103.98
<2250 kg	Reference	Windshield	−25.51
2251–5700 kg	19.64	Nose	−17.86
5701–27,000 kg	−146.31	Propeller	−2.12
27,001–272,000 kg	−195.27	Wing	121.86
>272,000 kg	−109.06	Fuselage	−15.05
Engine type			
Turbofan	reference	Landing gear	−2.05
Reciprocating	−34.91	Tail	387.91
Turbojet	−8.73	Lights	872.54
Turboprop	−23.75	Other	60.14
Phase of flight		Unknown	−41.26
Approach	Reference		
Climb	57.41	*Engine strikes and ingestion*	
		Ingested – 1 engine	5970.17
Descent	116	Ingested – >1 engine	10726.25
En route	224.47	Not ingest. – 1 engine	78.21
Landing roll	−24.64	Not ingest. >1 engine	49.98
Take-off run	2.16	*# of birds struck*	
Parked	−29.27	1	reference
Taxi	−26.48	2–10	22.94
Bird size		11–100	103
Small	−1257.51	>100	1553.77
Medium	−1166.72		
Large	Reference		

Note: All entries are expressed in dollars.

intakes, as well as the propeller blades deflecting bird debris away from the interior of the engine. Although we include indicators for engine ingestion events, it is likely to be the case that our engine types are correlated with ingestion, such that the engine type coefficients may be partially capturing the different likelihoods of ingestion inherent to each engine type. This suggests that our ingestion effect variables are not perfectly controlling for the event of engine ingestion, and that some uncontrolled correlation remains between variables.

Phase of flight

First, consider those phases in which the vehicle is on the ground (i.e. parked, taxi, and landing roll), which all involve the aircraft traveling at low or no speed. These lower speeds will translate into much lower impact force generated from any given strike, and because birds will be striking the plane with less total force, the reductions in expected repair costs of a damaging strike are consistent with our initial expectations regarding the average partial effects (Table 3, Fig. 2). However, we do observe increases in expected repair costs associated with several phases relative to approach. A strike which occurs during any of the three phases of flight in which the aircraft is at a substantial altitude (i.e. climb, descent, or en route) is associated with an increase in the expected costs of repairing any damages. This is consistent with our expectations; a plane at cruising altitude and speed will be traveling at a very high speed, and any midair collision with a foreign object will result in tremendous impact force. Any such impact would be highly likely to result in an adverse effect on the plane, necessitating some direct repair costs via inspection to verify or correct any resultant damages. In addition, we see an increase in repair costs stemming from strikes occurring during a take-off run, perhaps because of the critical nature of this phase of the flight and the fact that engines typically produce relatively high power at this time (Dolbeer et al., 2013).

Struck components

Interpreting our "components struck" coefficients requires some care, in that each of these components is in relation to "this component was not struck." We see substantial increases stemming from strikes to several easily damaged components, such as the plane's radome (nose cone), wing, tail, and lights (Fig. 3). In each case, any strike requires inspection and maintenance, as well as a large likelihood that the part will need repair or replacement. We also note that our two categories indicating that a strike occurred to an uncertain or unknown component (other and unknown) are not directly interpretable. Additionally, although several of the estimated partial effects associated with struck components were negative, the standard errors of the associated coefficients in the probit and log-linear models were quite large, preventing strong inferences from being made about the true impact of those struck components.

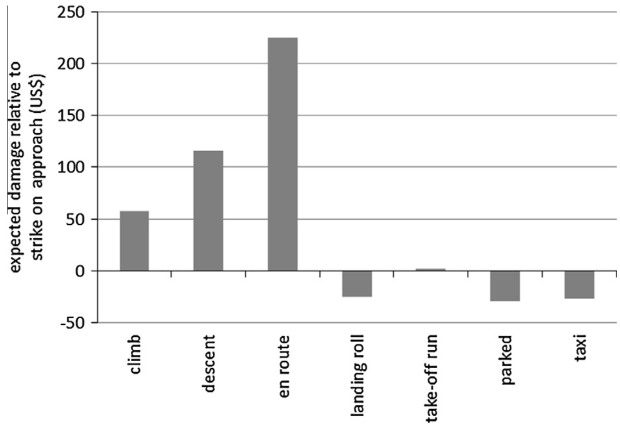

Fig. 2. Average partial effects associated with strikes during phases of flight. Each is measured relative to a strike during approach.

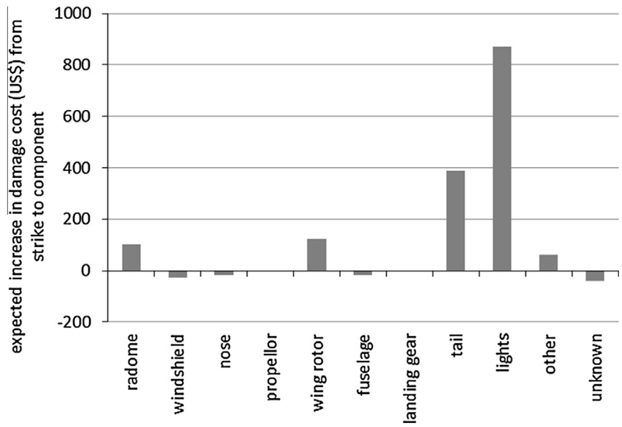

Fig. 3. Average partial effects associated with a strike to each component.

Ingestion effects

The baseline for these categorical variables is "no engines struck and no ingestion has occurred"; each of the reported coefficients is adjusting the estimated repair costs of a damaging strike in a logical fashion. That is, when ingestion has occurred, we see very large increases in the expected costs of repair, whereas we see much more modest increases when ingestion is not a factor but an engine has been struck, regardless of whether the strike involved one or more than one engine. This is consistent with the fact that a bird entering an engine represents a potentially catastrophic engine failure, which is a very costly event. Not only is the engine itself damaged, but there is a relatively high probability that such an event will result in other forms of repair costs to other parts of the aircraft (especially if the engine failure results in a crash-related event).

Bird size

Our reference category in this group is strikes involving large birds, which would be expected to generate larger repair costs than strikes involving a small or medium sized bird. This is consistent with our understanding of how the impact force of a bird strike is calculated (see MacKinnon et al., 2001); because impact force is proportional to a bird's mass, a larger bird will generate a larger impact force than will a smaller bird, all else equal. This expectation is borne out in our results, in that we see substantial decreases in the estimated repair costs associated with either small or medium sized birds relative to strikes involving large birds (see also Dolbeer and Wright, 2009; DeVault et al., 2011).

One point worth mentioning is that there is some imprecision and embedded measurement error regarding the size of birds struck. Although some estimates of bird size are corrected at a later stage based on the particular species involved, estimates of bird size within some strike reports are based upon the subjective measure of the bird's size drawn from the strike reporter's best guess about the size of the involved wildlife, which may vary considerably between different reporters and therefore different observations. Many reported strikes do list the specific species involved and, in principle, it is possible to

include a measure of species mass rather than the categorical size variables. However, a substantial number of observations do not include the specific species, and the size of the sample would be limited as a result. Additionally, inclusion of the categorical size variables allows a very flexible relationship between bird size and damage, whereas the including a single, continuous mass variable would impose a more restrictive relationship.

Number of birds

When considering the number of birds involved in a strike event, recall that our reference group is a strike between an aircraft and a single bird. The average partial effects calculated for striking more than one bird during a single event indicate that striking a larger number of birds directly increases the estimated costs of repair stemming from a damaging bird strike. In particular, we see modest increases in repair costs for strikes involving more than one bird but less than ten birds, more sizable increases when between 11 and 100 birds are involved, and a substantial hike in costs for strikes with large flocks of greater than 100 individual birds (see also DeVault et al., 2011).

Conclusions

In broad terms, the purpose of our research is to more accurately measure the scope and magnitude of the bird strike problem in monetary terms, with an eye towards providing better information for wildlife damage cost-benefit analyses and damage mitigation strategies. We estimate the probability of a non-zero damage cost, as well as the expected magnitude of damage cost given that a damaging strike has occurred. We then assemble a composite expected cost of the strike for those observations that indicate damage, which could be used in the future to interpolate strike costs for strike reports that do not report a cost. The current voluntary strike reporting system is known to underreport both the occurrence of strikes as well as the explicit damage or repair costs (Dolbeer et al., 2013). Therefore, any method which may be able to improve the data quality is valuable for decisions or analyses that rely upon the data. Given that wildlife management resources are finite, anything which allows them to be directed more effectively will improve efficiency of operations throughout the US aviation system. In addition, because there are a number of different stakeholders involved in wildlife damage mitigation efforts at airports, improving the quality of shared information available to the various decision makers will result in more effective collaborations.

There are several limitations to our analysis. We have assumed very simple functional forms for each component of our model, using only categorical variables, and it may be the case that there are aspects of the behavior of repair costs that this categorical approach fails to capture. There are also measurement problems associated with estimates of bird size and bird numbers. As they appear in the NWSD data, bird size is sometimes a subjective measure and estimates of the number of birds struck are subject to the inherent difficulties of such estimates. Additionally, strikes are sometimes reported based on feathers and other residue left from the strike. In such cases, it can be difficult to properly identify the number of birds struck. There are also many choices to be made about which variables should be included in the models. When there is a choice to include additional variables that were correlated with already-included variables but that were also missing for many observations, we favor exclusion to minimize issues with multicollinearity and maximize the sample size. We acknowledge that there is some degree of subjectivity to this approach, but more formal methods of model selection are not fully capable of considering these tradeoffs. Finally, although we suggest that the model can be used to interpolate missing data, this should be done with caution. The models appear to fit the sample data well, but as more data becomes available, forecasting performance should be carefully evaluated based on new, out-of-sample data.

The framework we provide is ultimately useful for two reasons. First, it provides a better understanding of how the probability and extent of damage are affected by the characteristics of a strike. Second, the model can be used to estimate the cost of the substantial number of strikes for which the actual cost is unreported. Thus, the goal of future work will be to better assess how the cost of bird strikes varies across airports and over time by using our model to alleviate the problem of underreporting of strike costs that is present in the current data. Ultimately, this will allow research and management resources to be devoted where and when the highest costs occur and the potential benefits of mitigation efforts are the greatest.

References

Allan, J.R., Orosz, A.P., 2001. The costs of bird strikes to commercial aviation. 2001 Bird Strike Committee-USA/Canada, Third Joint Annual Meeting, Calgary, AB, p. 2.

Blackwell, B.F., DeVault, T.L., Fernández-Juricic, E., Dolbeer, R.A., 2009. Wildlife collisions with aircraft: a missing component of land-use planning on and near airports? Landscape Urban Plan. 93 (1), 1–9. http://dx.doi.org/10.1016/j.landurbplan.2009.07.005.

Cleary, E.C., Dolbeer, R.A., 2005. Wildlife hazard management at airports, a manual for airport operators, second ed. Federal Aviation Administration, Office of Airport Safety and Standards, Washington, DC, USA, p. 348.

DeVault, T.L., Belant, J.L., Blackwell, B.F., Seamans, T.W., 2011. Interspecific variation in wildlife hazards to aircraft: implications for airport wildlife management. Wildlife Soc. Bull. 35 (4), 394–402. http://dx.doi.org/10.1002/wsb.75.

DeVault, T.L., Blackwell, B.F., Belant, J.L. (Eds.), 2013. Wildlife in Airport Environments: Preventing Animal-Aircraft Collisions Through Science-based Management. Johns Hopkins University Press, Baltimore, Maryland, USA, ISBN-13: 9781421410821.

Dolbeer, R.A. 2009. Trends in wildlife strike reporting, part 1—voluntary system, 1990–2008, U.S. Department of Transportation, Federal Aviation Administration Report, DOT/FAA/AR-09/65, Washington, D.C., USA.

Dolbeer, R.A., 2013. The history of wildlife strikes and management at airports. Pages 1–6. In: DeVault, T.L., Blackwell, B.F., Belant, J.L. (Eds.), Wildlife in Airport Environments: Preventing Animal-Aircraft Collisions through Science-based Management. John Hopkins University Press, Baltimore, MD, USA, p. 181.
Dolbeer, R.A., Wright, S.E., 2009. Safety management systems: how useful will the FAA National Wildlife Strike Database be? Human-Wildlife Conflicts 3 (2), 167–178.
Dolbeer, R.A., Wright, S.E., Clearly, E.C., 2000. Ranking the hazard level of wildlife species to aviation. Wildlife Soc. Bull. 28 (2), 372–378.
Dolbeer, R.A., Wright, S.E., Weller, J., Begier, M.J., 2013. Wildlife strikes to civil aircraft in the United States, 1990–2012. U.S. Department of Transportation, Federal Aviation Administration, Office of Airport Safety and Standards, Serial Report No. 19, Washington, DC., USA.
Federal Aviation Administration [FAA], 2007. Hazardous wildlife attractants on or near airports. Advisory Circular, U.S. Department of Transportation. 150/5200-33B, Washington, D.C., USA.
Greene, W.H., 2003. Econometric Analysis. Pearson Education Inc., Upper Saddle River, New Jersey, USA, 1026pp.
MacKinnon, B., Sowden, R., Dudley, S., (Eds.), 2001. Sharing the skies: an aviation guide to the management of wildlife hazards. Transport Canada, Aviation Publishing Division, AARA, 5th Floor, Tower C, 330 Sparks Street, Ottawa, Ontario, K1A 0N8, Canada. 316p.
McDonald, J.F., Moffitt, R.A., 1980. The uses of tobit analysis. Rev. Econ. Statist. 62 (2), 318–321.
White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica 48 (4), 817–838.
Wright, S.E., Dolbeer, R.A. 2005. Percentage of wildlife strikes reported and species identified under a voluntary reporting system. In: 2005 Bird Strike Committee-USA/Canada 7th Annual Meeting, Vancouver, BC, pp. 11.
Zakrajsek, E.J., Bisonette, J.A., 2005. Ranking the risk of wildlife species hazardous to Military Aircraft. Wildlife Soc. Bull. 33 (1), 258–264.