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Assessing economic performance and aviation accidents using zero-inflated and over-dispersed panel data models

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ABSTRACT

This paper explores the link between air transport safety and profitability. Traditionally, the empirical literature has used Poisson regression models to estimate the expected number of accidents given the profitability of the airline. However, there are two major deficiencies in this analysis related to the statistical properties of the data. First, the equi-dispersion assumed in Poisson models hardly holds in the airline data. Second, accidents are rare cases, so the data has an excess of zeros. In this paper, we propose the use of a zero-inflated negative binomial model to deal with these shortcomings. Our results show several interesting facts. On the one hand, they show that airlines with higher levels of profitability are less likely to have an accident. On the other hand, when an accident occurs, there is a higher expected number of accidents in airlines with higher profitability. Finally, the severity of an accident has an inverse relationship with profitability.

1. Introduction

Safety is a major concern in all industries, but it is especially relevant in air transport. The repercussions of an aeroplane accident on markets have made safety a key goal for the industry, which constantly seeks to reduce the number of incidents and accidents (Liao, 2015).[1]

When homogenizing the numbers, air transport is one of the safest travel modes (see, for instance, Evans, 2003). Moreover, most of the accidents in air transport are related to general aviation where the accident and fatality rates are around 50 and 53 times higher, respectively, than in commercial aviation (Sobieralski, 2013). However, even when, statistically, commercial aviation is a safe transport mode, the significant impact of a single fatal accident in terms of fatalities generates insecurities in the population.

Since the deregulation of the air transport markets in 1978, one of the main concerns of regulators and researchers has been a possible trade-off between profitability and safety because its relationship is particularly relevant in sectors that employ high technology. Are the managers of struggling airlines willing to take more risks when their organization is in the red? This question has previously been addressed in the literature, without consensus. See, for instance, Rose (1990), who found that airline profitability is directly correlated with airline safety, and Madsen (2013), who demonstrated a positive or negative relationship depending on the firms' profitability targets.

In the commercial air transport market, the information regarding safety control belongs to airlines companies; this situation generates an asymmetric information relationship between airlines and regulators. The latter needs to establish measures in order to reduce this asymmetry. However, while regulation can establish minimum requirements in terms of safety, company stakeholders have their own incentives to ensure that they are perceived as safe. The issue of air transport safety generates implications for management systems, companies and financial markets.

First, regarding safety management systems, the negative impacts of

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[1] According to the Glossary for Transport Statistics (2019), an air transport accident can be defined as an event during aircraft operation that takes places between the time a person boards the aircraft with the intention of flight until the moment that every person has disembarked. Moreover, to meet the definition, the person has to be seriously or fatally injured, or the aircraft sustain damage or structural failure. Separately, an incident is an event, other than an accident, that is associated with the operation of an aircraft that affects, or could affect, the safety of this operation.

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an accident have meant that part of technological development has been focused on improving safety.[2] In fact, technological progress is one of the key variables that explain the reduction in the number of accidents and incidents (Oster Jr et al., 2013). Moreover, the joint action of governments and the airline industry through the investigation of an accident and regulation systems has also improved airline safety operations (Stolzer et al., 2016).

Second, regarding air transport demand, an increase in the air transport fatality rate leads to a fall in overall demand for flights (Liu and Zeng, 2007). This loss in the overall number of passengers is also accompanied by a loss of trust from consumers. Safety perception is an important variable for airlines in order to maintain consumer trust, because an accident can significantly affect a company's future. For the airline industry, their safety reputation affects consumers' choice of airline (Siomkos, 2000), and even of particular flights (Molin et al., 2017).

And third, the aftermath of an accident not only affects airlines in terms of passengers' choice, but also the financial markets. Noronha and Singal (2004) showed that financially strong airlines measured by bond ratings are more likely to have an accident. Nevertheless, these authors also stated that bond ratings are sticky and not available for all the companies. Additionally, when an accident happens, airline stock markets experience greater volatility (Akyildirim et al., 2020). Specifically, this volatility is positively correlated with the degree of fatality (Ho et al., 2013). In fact, the impact of airline accidents on stock markets goes beyond airlines, by also affecting manufacturers (Akyildirim et al., 2021), and can even spread to the global economy (Kaplanski and Levy, 2010).

The main objective of this paper is to focus on the third implication of safety on financial markets, and to address the following question: 'How to improve safety management and regulation if there is a link between safety and profitability?'. The use of profits as economic performance has been usually used in the literature as a proxy of the short-term financial distress (see for instance: Golbe, 1986; Rose, 1990 or Fardnia et al., 2020). Operating profits plays a relevant role in influencing a company's stock valuation. It serves as a reliable indicator of the company's prospective earnings and, consequently, its stock price. Shareholders typically exhibit a preference for companies boasting robust operating profits, leading to a rise in stock price.

To respond to the aforementioned question, we analyze if companies with higher profits are safer not only for accidents, but also for fatalities and incidents. Furthermore, we consider the statistical side of accident variable, which is a count outcome and has a large proportion of zeros. These characteristics allow us to define a model that assumes a mixture of two classes of outcomes: those generated by the count data model (e.g., Poisson or Negative Binomial, among others), and another group, whose outcome is zero or not, which is modelled by a logistic regression model. To date, econometric methods used to investigate safety and profit relationship neglect heterogeneity and the excess of zeros, and, moreover, are based on equi-dispersed approaches (variance equal to the mean). Count data often display over-dispersion (variance greater than the mean) and inappropriate imposition of Poisson regressions may lead to invalid inference.[3]

Therefore, this paper contributes to the airline accidents literature by employing a latent class model that accounts for over-dispersion and excess-zeros in a count data panel framework. The model we propose is the zero-inflated Negative Binomial model (ZINB), which has important applications for this type of data. The data distribution for this model combines the logit distribution and the Negative Binomial distribution in a mixed process. This allows us to investigate, firstly, the likelihood of an accident occurring, and secondly, the expected number of accidents. It is also noteworthy that this approach contains two sources of heterogeneity: latent heterogeneity and the mixing of latent classes.

To do this, we use information related to a panel data for US' companies and quarterly data between 1991 and 2018.

This paper is organized as follows. Section 2 presents the literature review. Methodology is explained in Section 3. Section 4 show data, results and the diagnostic tests and Section 5 discusses the main results. Finally, conclusions are presented in the last Section.

2. Safety and profitability

The relationship between airline safety and profitability has been studied previously in the literature, especially after the deregulation of the market. Table 1 summarizes these studies indicating the authors and year of publication, country and period under study, methodology, variables used, and results about the relation between safety and profitability. The papers in Table 1 can be split into two main and general approaches: panel and non-panel data models. Next, we briefly comment on their results.

2.1. Non-panel data approaches

In this subsection we describe the general methods mainly used to assess safety and profitability, by focusing on non-panel data approaches. Econometric methods used in this context were structural equations and time series methods, but also count data models in cross-section.

Golbe (1986) studied the relationship between profits and safety in the prederegulated U.S. airline industry. Two model approximation were used. On the one hand, the structural equations, on the other, time series analysis. The author could not find any significant link between these variables. A long time period from 1938 to 1994 was analyzed by Adrangi et al. (1997). These authors used a Granger causality approach and tested different financial variables but none of the variables tested proved to be significant. In a worldwide context, Fardnia et al. (2020) analyzed 110 airlines in 26 countries to study the relationship between profits and safety performance. The authors used a pooled data framework, using both OLS and Poisson regressions. Their results showed a negative relationship between profitability and safety performance. Moreover, the regulatory systems and the overall economic performance of the countries were also related with safety. Further, these authors did not find any significant change following the deregulation of airlines.

In an alternative approach, Kalemba and Campa–Planas (2019) analyzed the impact of safety on financial results by using regular panel data estimation. The authors showed that safety performance has a positive impact on financial results. In fact, this positive impact of safety performance on financial results can also be transmitted to manufacturers. Akyildirim et al. (2021) analyzed the relationship between an airline accident and manufacturers' finance. Specifically, the authors employed a GARCH model to study the link between an accident and its economic impact on an engine manufacturers' financial results. The authors found that an accident results in an immediate loss of 1.64% on average, and its effects persist even if the manufacturer is not in any way responsible for the accident.

2.2. Panel data models

In this subsection we describe the panel data models used to investigate the relationship under study, predominantly drawing on count data models in the panel data framework.

Panel count data models have been the most common methodology used in the literature to evaluate the existence of a link between

[2] For example, advanced GPS location (the Automatic Dependent Surveillance-Broadcast, ADS-B system), improved materials, enhanced engines, improved navigation and communication systems, enhanced weather forecasting or improved safety procedures.

[3] One of the consequences of over-dispersion is the standard deviation of parameter estimates downward biased and significance of predictor variables upward biased (see Ismail and Jemain, 2007).

Table 1
Empirical studies on the link between safety and profitability.

Authors (year)	Country	Period	Methodology	Variables	Link (safety/profitability)
Golbe (1986)	U.S.A.	1952–1972	Structural Equations and Time Series	Fatality rates, operating profits, net operating profits	No
Rose (1990)	U.S.A.	1957–1986	Panel data with Poisson	Accident rate, operating margin, average stage length, operating experience, international flights, Alaskan carriers	Yes
Adrangi et al. (1997)	U.S.A.	1938–1994	Bivariate Granger causality regressions	Fatalities per revenues, fatalities per departures, operating profits, net operating profits	No
Dionne et al. (1997)	Canada	1976–1987	Panel data with Poisson	Accidents, hours, speed, weather, time, size, operating margin, debt over equity, working capital	Yes
Noronha and Singal (2004)	U.S.A.	1983–1998	Panel data with Poisson	Accident rate, bond ratings, departures international revenues, time	Yes
Raghavan and Rhoades (2005)	U.S.A.	1955–2002	OLS and Poisson regressions	Accident rate, experience, stage length, operating profit margin, time	Yes
Madsen (2013)	U.S.A.	1990–2007	Panel data with Poisson	Accidents, Profitability, time departures, stage length, debt ratio, maintenance, domestic flights, bankruptcy protection	Yes
Wang et al. (2013)	U.S.A.	1991–2008	Panel data with Poisson and Structural equations	Accident rate, Altman's Z-score, safety investment, departures, average stage length, international flights, salaries of flight personnel, salary of maintenance personnel	No
Kalemba and Campa–Planas (2019)	Worldwide	2011–2015	Panel data	Return on Investment, revenues, JACDEc index, number of passengers, load factor	No
Fardnia et al. (2020)	Worldwide	1990–2009	OLS and Poisson regressions	Accident rate, liquidity, Leverage, activity, Profitability, GDP, departures, unemployment rate, legal variables	Yes
Akyildirim et al. (2021)	Worldwide	1995–2018	GARCH family	Market cap, returns, stock price, turnover ratio, Amilhud ratio, benchmark index	–

profitability and air transport safety, since Rose's seminal paper (1990).[4]

The main count data model used was the Poisson panel data model. For example, Rose (1990) used a panel Poisson regression. The author stated that the use of contemporary variables could create inverse relationship problems. To avoid this problem, the author proposed the use of lagged data for the profit variable, and subsequently found a positive relationship between safety and profits (measured as the operative margin). Moreover, author showed that this relationship was stronger in small airlines, while it was marginal on larger ones. Raghavan and Rhoades (2005) used both OLS and Poisson regressions, and found similar results. Similar to the aforementioned studies, Dionne et al. (1997) analyzed the situation for the Canadian market, but also added additional financial variables. These authors also found an inverse relationship that is stronger in small airlines. Moreover, their results showed that maintenance expenditure was directly related to air transport safety.

Different variables have also been used in the literature. For example, Wang et al. (2013) used a combination of structural models and Poisson regression with panel data. These authors explicitly modelled an indirect inverse relationship between financial condition (measured as a Z score) and safety through their impact on safety investment. The paper shows that safety investment is negatively related with accidents, while accidents positively affect safety investment. However, the authors could not find any direct link between financial conditions and safety. Noronha and Singal (2004) employed bond ratings and 'mishaps' as a proxy for financial health and safety respectively. The authors found that airlines with higher quality bond ratings are less likely to experience mishaps. Madsen (2013), on the other hand, employed not only current financial data, but also the profitability aspiration of airlines. This paper evidenced a negative relationship between financial and accidents. Moreover, it found that performing below airline aspirations is related to a higher number of accidents, while performing above aspirations implies less. However, the author could not find evidence about the link between profitability and safety using current financial data.

However, in this literature and to our knowledge, these papers have only used Poisson distributions, and none investigate the profit and safety relationship considering zero-inflated and over-dispersed count data models.

In this paper, airline safety is analyzed depending on profitability (among other factors). It is worth noting that the previous literature (Rose, 1990; Wang et al., 2013; Madsen, 2013; Akyildirim et al., 2021; among others) has studied this relationship in this direction of causality. As Akyildirim et al. (2021) argue, and as, for example, Rose (1990) effectively proves, reverse causality is eliminated by using lagged benefit measures.

3. Methodology

As seen in Section 2, recent empirical literature analyzing safety and profitability has mainly focused on Poisson panel data models.

However, while regular count data models can model rare events, in the case of air transport, fortunately, the probability of an accident occurring is very rare. This means that the distribution of accidents shows an excess of zeros, which should be considered. Moreover, the commonly used Poisson distribution presents the restriction of equal mean and variance, which barely holds in air transport accident data. For example, it is worth noting that data on accidents show more variation than implied Poisson distribution. Thus, over-dispersion should be accounted for when dealing with air transport safety.[5]

In this context, such over-dispersion can be factored in by using

[4] From the pioneer study of Hausman et al. (1984), panel count data models can be seen in many applications (see, for example, Cincera, 1997; Montalvo, 1997, among others). Many authors have highlighted the advantages of using panel count model over analysis based on cross-section or time series data. See Karlaftis and Tarko (1998), Hsiao (2003), Cameron and Trivedi (2005), and Winkelmann (2008), among others.

[5] The common interpretation of over-dispersion is that it can be related to neglected unobserved heterogeneity (Cameron and Trivedi, 2013, p.111). Particularly, unobserved individual heterogeneity may emerge when the variables included in the model may not be able to capture all the dependent variables' heterogeneity: in our case, accidents. This unobserved heterogeneity might reflect a specification error, such as omitted exogenous variables. Therefore, both unobserved heterogeneity and over-dispersion can lead to biased results.

models with different assumptions about how the variance changes with the mean. Between these two elements, for example, the mean-variance relationship can be appropriately described by the Negative Binomial distribution (e.g., McCullagh and Nelder, 1989), although there are other approaches such as quasi-likelihood-based Poisson models (e.g., Wedderburn, 1974) or random effects models (e.g., Bolker et al., 2009) that can be also used. Therefore, we propose using the zero-inflated Negative Binomial (ZINB) model, which is usually adequate for allowing excess-zeros and over-dispersion. This model assumes that excess-zero counts can be modelled from a logit model, with the remaining counts coming from the Negative Binomial model to account for over-dispersion. ZINB allows us to have a large fraction of zeros without restricting the range of outcomes. See Long (1997) and Cameron and Trivedi (2005) for a discussion of the zero-inflated count data models.

Below, we define some notation.

Let y_{it} be the number of accidents (but also, it can be defined as the number of fatalities or incidents) ($y_{it} = 0,1, \ldots,n$) for firm i ($i = 1,2, \ldots,N$) in period t ($t = 1,2, \ldots,T$), x_{it} is a column vector of order k_1x1 of covariates potentially explaining $y_{it} > 0$, z_{it} is a column vector of order k_2x1 of covariates explaining $y_{it} = 0$. Furthermore, firm-specific and time-specific fixed-effects are defined by ν_i and ξ_t, respectively. No assumptions on individual effects are made, and they are treated as nuisance parameters.

Next, we define the ZINB model in a panel data context with both firm and time fixed-effects. We extend Lambert (1992)'s notation by including fixed effects, considering the mean number of accidents, λ_{it}, and the probability of $y_{it} = 0$ obtained by a logistic distribution, F_{it}, such as:

$$\lambda_{it} = \exp\left(x_{it}^{'}\beta + v_i + \xi_t\right), \tag{1}$$

$$F_{it} = \frac{\exp\left(z_{it}^{'}\theta + v_i + \xi_t\right)}{1 + exp\left(z_{it}^{'}\theta + v_i + \xi_t\right)}, \tag{2}$$

where β is a column vector of order k_1x1 of unknown parameters for the mean equation and θ is a column vector of order k_2x1 of unknown parameters for the probability equation, respectively.

ZINB model is defined by considering $y_{it}|\gamma_{it} \sim$ Poisson(γ_{it}), where $\gamma_{it}|\delta_i \sim$ Gamma(λ_{it}, δ_i), being δ_i the dispersion parameter of the Negative Binomial distribution, which can be assumed as a generalization of the Poisson regression. Thus, $y_{it} = 0$ with probability F_{it} and $y_{it} \sim$ Gamma (λ_{it}, δ_i) with probability $1 - F_{it}$. This specification allows flexible fixed individual effects, whereas panel data with random effects are more restrictive and impose strong assumptions on individual effects.

As it can be seen, the ZINB specification incorporates a parameter to model the overdispersion. In this sense, by assuming the Negative Binomial model, we are considering that the operation and financial data of each carrier might not capture all heterogeneous causes of accidents. The ZINB models fit over-dispersed count data with an excess of zero counts.

The log likelihood maximized is defined by:

$$\begin{aligned} \ln L = & \sum_{i \in S} w_i \ln\{F_{it} + (1 - F_{it}) p_{it}^{m_i}\} \\ & + \sum_{i \notin S} w_i \{\ln(1 - F_{it}) + ln\,\Gamma(m_i + y_{it}) - ln\,\Gamma(y_{it} + 1) \\ & - ln\,\Gamma(m_i) + m_i\, ln\, p_{it} + y_{it} \ln(1 - p_{it})\}, \end{aligned} \tag{3}$$

where w_i is the weight for the ith group, S is the set of observations for which the observed outcome $y_{it} = 0$, $p_{it} = 1/(1 + \delta_i\lambda_{it})$ and $m_i = 1/\delta_i$. The mean is

$E[y_{it}] = (1 - F_{it})\lambda_{it}$ and the variance is $Var[y_{it}] = (1 - F_{it})\lambda_{it}\{1 + \lambda_{it}(F_{it} + \delta_i)\}$.

Following Stram and Lee (1994, 1995), over-dispersion can be tested in Negative Binomial models using the likelihood ratio (LR) test for the null hypothesis: H_0: $\delta = 0$ against the alternative hypothesis H_1: $\delta \neq 0$. The LR statistic is defined as $LR = 2(\ln L_1 - \ln L_0)$, where $\ln L_1$ and $\ln L_0$ are the log likelihood values under H_1 and H_0, respectively. This statistic follows a chi-square distribution with one degree of freedom. For testing the ZINB model versus Negative Binomial model, the Vuong test (Vuong, 1989) can be calculated. This statistic compares the probability mass functions of two models following a standard normal distribution and choosing (or not) one the models as the "closer" to the actual one. Finally, Bayesian Schwarz criteria (BIC) can be used to compare the models' performance, penalizing those with a larger number of parameters (k) and larger sample size (n), $BIC = -2\ln L + k \ln(n)$.

4. Empirical analysis

4.1. Data

This study focuses on the domestic aviation US market because the publicly available data outperforms most other world markets.

The information we use has been extracted from several databases such as the Bureau of Transportation Statistics (BTS), the Federal Aviation Administration (FAA) and the National Transportation Safety Board. These sources of information provide comprehensive databases that are publicly available online.

Using information regarding above data sources including both main and low-cost carriers, an unbalanced panel data-set containing quarterly data for 94 passengers airlines and 28 years (1991–2018) is built. The data-set used excludes private jet companies and airlines that did not appear for at least three full years in the sample.

Next, we define the variables employed in this study by distinguishing between endogenous and exogenous variables that will be used in the modelling.

4.1.1. Accidents, fatalities and incidents as dependent variables

The number of accidents, fatalities and incidents are measured as the sum of events of airline i in quarter t. These variables have been previously used in the literature (see for instance, Rose, 1990; Madsen, 2013; among others).

Data about each accident was obtained from the Aviation Accident Database of the National Transportation Safety Board.[6] This database contains all accidents and selected incidents. The full incident database was obtained from the Federal Aviation Administration Accident and Incident Data System (AIDS).[7]

The total number of available observations for accidents is 4355 for all airlines and years. Regarding fatalities and incidents, the number of observations was 372 and 4357, respectively. These observations include only those airlines that have had at least one accident, fatality or incident throughout the entire analyzed sample. In the case of fatalities, there are only 11 airlines involved.

4.1.2. Determinants or exogenous variables

As determinants or explanatory variables for accidents, fatalities and incidents we use several economic and financial data but also operating data factors, which have also been used in a number of papers, such as Rose (1990), Madsen (2013), and Wang et al. (2013); among others.

These variables can be characterized as follows. On the one hand, operating data used is related to the average distance between airports and performed departures. These data were obtained from the T-100 Domestic Segment (US Carriers)[8] database, which is part of the Form 41 Traffic. This database contains aircraft type per airline per airport pair level data that had to be aggregated at airline level on a quarterly basis.

[6] See https://data.ntsb.gov/avdata.

[7] See https://www.asias.faa.gov/apex/f.

[8] See https://www.transtats.bts.gov/Fields.asp?gnoyr_VQ=GEE.

On the other hand, financial data for each carrier was obtained from Schedule P-1.2,[9] which is part of the Form 41 Financial Data. This database is provided at airline level on a quarterly basis.

It is noteworthy that some economic variables are transformed. For example, the profit margin, which measures the difference between income and costs in relation to the airline's total costs, is calculated as follows:

$$Profit\ margin = \frac{Total\ incomes\ -\ Total\ operational\ costs}{Total\ operational\ costs}.$$

It is also worth noting that one-lagged profit margin is used to avoid endogeneity problems (see, for example, Rose, 1990; Wang et al., 2013; Akyildirim et al., 2021). To check the reverse causality problem relating to profit and accidents probability, we have run the Juodis et al. (2021) Granger non-causality test. Results for the half-panel Jackknife estimator show that there is no evidence to reject the null hypothesis that accidents do not cause profits (p-value = 0.891).

Cost flight (in thousands of dollars) is used to control for the flight cost during the previous period. However, this variable is normalized during the regressions representing the deviation of the airline company's costs from the sector's average cost during that period. The maintenance cost (in thousands of dollars) represents the flight costs dedicated to that field; some variations in this variable has been used in Madsen (2013) and Wang et al. (2013). Average distance measures the average route distance (in miles) of each airline. Finally, performed departures measures the number of departures of each airline (see, for instance, Noronha and Singal, 2004; Madsen, 2013, or Akyildirim et al., 2021; among others).

Additionally, control variables are utilized in the estimation process, with technological progress being controlled by incorporating a time trend. The type of company is also controlled using a dummy variable to distinguish between low-cost carriers (LCC) and main carriers. Furthermore, control is applied for 11-S, as well as seasonal and airline fixed effects using dummy variables.

Table 2 summarizes the endogenous (Panel A) and determinant (Panel B) variables used in this study for the overall sample, main carriers and, finally, LCC. In general, it can be observed that accidents, fatalities and incidents have standard deviations (s.d.) greater than the mean, which is a characteristic related to over-dispersed data. Furthermore, no significant differences are observed between the average number of LCC accidents and main carriers (Kolmogorov-Smirnov test, p-value = 0.825).

4.2. Estimation results

In this section, we show results corresponding to the estimation for passenger airlines' number of accidents, fatalities and incidents.

In Tables 3 and 6, we include several model results for comparative purposes. Therefore, we show results for both the classic Poisson and Negative Binomial (NB) models, but also for those models which consider the relevance of zeros in the dependent variables such as zero-inflated Poisson (ZIP) and Negative Binomial (ZINB) models.

It is noteworthy that ZIP and ZINB models converged only for the number of accidents' model. This might be explained by the high variability in the distribution of fatalities and incidents. In those cases, we only present results for the classic Poisson and NB models.

The general results we obtain indicate that, while most of the literature has focused on the Poisson regression (Rose, 1990; Dionne et al., 1997; Noronha and Singal, 2004; among others), over-dispersion exists in the air transport industry. This conclusion is based on the fact that the over-dispersion likelihood ratio test rejects the null hypothesis of no over-dispersion (e.g., $\delta = 0$). This means that the Negative Binomial specification suits the data better than the Poisson models.

Next, we briefly comment on the factors that affect the endogenous variables by distinguishing two sub-sections: the number of accidents, and fatalities and incidents.

4.2.1. Determinants of the number of accidents

Table 3 shows the estimation output for the number of accidents including some lagged variables and distinguishing two panel results, considering several panel count data models with fixed-effects. Table 3 (Panel A) includes how the coefficients can explain the excess of zeros. This means that a positive value implies that the probability of having an accident diminishes if the value of the variable grows. Table 3 (Panel B) explains the number of accidents after discounting the zero cases. Looking at the standard Poisson and Negative Binomial models, we note an interesting result: those companies with higher operative profits relative to their operative costs in the previous period ($Profit\ margin_{t-1}$) have a larger number of expected accidents. However, this result is biased by the existence of an excess of zeros in the sample.

After applying a zero-inflated regression we can disentangle the effect of each variable in two. On the one hand, Panel A shows that those companies with positive profit margins are more likely to have more zeros, i.e., the probability of having an accident is lower for those companies. On the other hand, we can observe a positive and significant coefficient for the profit margin in Panel B. This means that, after an accident, the companies with great profit margins are expected to have more accidents.

Another surprising result in the ZIP and ZINB models is that those companies with cost levels per flight above the average have greater probabilities of having an accident (a negative sign on Panel A). However, these costs do not influence the expected number of accidents (Panel B). On the other hand, standard Poisson and Negative Binomial models might lead us to expect a higher number of accidents in companies with higher costs. The maintenance cost per flight does not seem significant either in the inflate of zeros nor in the number of accidents. Neither is distance significant, either in the probability of an accident or the expected number of them. Additionally, under zero-inflated models, a high number of departures increase the likelihood of having accidents, but not the expected number of them. Again, standard Poisson and Negative Binomial.

models only predict the expected number of accidents to increase as departures increase. Finally, we included a dummy to control for 11-S, which is significant, and a dummy to control for LCC, which is not.

While the use of zero-inflated regression can help us to understand the results, the model needs to be validated. To test the validity of the model, two different metrics are used. Firstly, a Vuong test, in which the null hypothesis is that standard Poisson and Negative Binomial models are preferred to zero-inflated specifications. This hypothesis is rejected at 5% in both estimations. Additionally, the BIC criteria of both the standard and zero-inflated estimations are also compared, with the latter being preferred. Lastly, we check the sample's over-dispersion. To do so, a likelihood ratio test is conducted, rejecting the null hypothesis and confirming the existence of over-dispersion in the data. This means that, while most literature has employed Poisson models, the existence of over-dispersion implies that the Negative Binomial model better fits the data.

Table 4 shows the mean, standard deviation, skewness, kurtosis and percentiles (p_{25}, p_{50}, p_{75} and p_{90}) for the expected number of accidents obtained by the models. It is noteworthy that mean values are similar among estimated models, but differences are more important for higher percentiles.

To assess the prediction ability of estimated models, we split the sample in two parts. Firstly, we estimate the model (i.e., training-phase) using the first 20 years (from 1991 to 2010). Secondly, the estimation results obtained are used for prediction of the model using information corresponding to the remaining 8 years (i.e., prediction-phase), from 2011 to 2018. Table 5 displays the results of the predictive analysis showing statistic measures as the mean absolute error (MAE), the mean

[9] See https://transtats.bts.gov/releaseinfo.asp?6o=FMI&qv52ynB=qn6n.

Table 2
Summary statistics (period 1991–2018).

Variables	All carriers				Main carriers				LCC carriers			
	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
Panel A. Endogenous variables												
Number of accidents	0.103	0.382	0	5	0.110	0.395	0	5	0.082	0.340	0	5
Number of fatalities	0.167	4.044	0	156	0.224	4.687	0	156	0	0	0	0
Number of incidents	1.051	2.416	0	30	1.220	2.702	0	30	0.561	1.121	0	8
Panel B. Determinant variables												
Profit margin	0.037	0.766	−1	50.003	0.045	0.891	−1	50.003	0.027	0.161	−0.971	1.147
Cost per flight	74.7	799.61	0.72	36,453.5	93.49	926.91	0.84	36,453.5	20.79	36.57	0.72	631.02
Maintenance cost per flight	13.06	183.13	0.07	8339.5	16.63	213.99	0.075	8339.5	3.010	12.76	0.11	396.97
Average distance	1014.72	714.80	69.43	5658.04	1022.59	767.92	69.43	5658.04	992.95	532.79	92	4029.03
Performed departures	52,910.15	70,283.92	2	353,999	57,250.38	68,861.71	2	293,483	40,371.57	82,882	2	353,999

Table 3
Maximum likelihood estimates for passenger airlines accidents and several panel count data models with fixed-effects (period 1991–2018).

	Poisson	NB	ZIP	ZINB
Panel A: Inflate of zeros Profit margin$_{t-1}$			9.1199***	10.7587***
			[3.100]	[3.784]
Cost flight$_{t-1}$			−4.9061**	−7.3876*
			[2.384]	[4.181]
Maintenance cost$_{t-1}$			−0.0668	−0.0756
			[0.081]	[0.097]
log Average distance			0.0513	0.5017
			[0.802]	[1.653]
log Performed departures			−0.4327**	−0.6856**
			[0.200]	[0.316]
Technological progress			−0.0527	−0.0435
			[0.067]	[0.062]
LCC			0.9576	1.0035
			[0.933]	[1.112]
11-S			3.122**	3.241**
			[1.234]	[1.268]
Panel B: Number of accidents Profit margin$_{t-1}$	0.9699***	0.9363***	3.5786***	2.7146***
	[0.315]	[0.341]	[0.747]	[0.747]
Cost flight$_{t-1}$	0.2909**	0.2810**	0.2119	0.1440
	[0.120]	[0.125]	[0.151]	[0.134]
Maintenance cost$_{t-1}$	0.0001	0.0001	0.0001	−0.00005
	[0.001]	[0.001]	[0.001]	[0.001]
log Average distance	−0.1021	−0.0876	−0.4069	0.0643
	[0.314]	[0.327]	[0.368]	[0.372]
log Performed departures	0.3170**	0.3124**	0.1372	0.2108
	[0.148]	[0.154]	[0.164]	[0.165]
Technological progress	0.0086	0.0066	0.0044	−0.0063
	[0.009]	[0.010]	[0.009]	[0.010]
LCC	15.7097	15.5274	12.1286	12.2030
	[4099.213]	[3775.135]	[528.050]	[721.415]
11-S	0.0784	0.0496	1.123**	1.125**
	[0.363]	[0.360]	[0.499]	[0.165]
δ		0.4463***		0.3202***
		[0.1561]		[0.158]
Fixed-company effects	YES	YES	YES	YES
Fixed-time effects	YES	YES	YES	YES
Observations	4355	4355	4355	4355
Log likelihood	−1176.55	−1169.99	−1166.17	−1163.40
BIC	3090.45	3085.71	3077.33	3069.69
Vuong test			2.40***	1.89**

Standard errors in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

squared error (MSE), and the root mean squared error (RMSE) for all the models considered. The results show the predictive capacity of the ZINB model, which outperforms the others in statistical measurement terms, because it has the lowest values.

Table 4
Descriptive statistics for the expected number of accidents (period 1991–2018).

	Poisson	NB	ZIP	ZINB
mean	0.1049	0.1048	0.1007	0.1039
s.d.	0.1592	0.1585	0.1654	0.1594
skewness	2.4761	2.4444	3.0315	2.5326
kurtosis	9.7904	9.4958	19.5945	10.0901
*p*25	0.0082	0.0084	0.0064	0.0079
*p*50	0.0423	0.0423	0.0384	0.0417
*p*75	0.1256	0.1261	0.1285	0.1237
*p*99	0.7230	0.7194	0.7045	0.7506

Table 5
Predictive analysis for the models (period 2011–2018).

	Poisson	NB	ZIP	ZINB
MAE	6.5366	6.8481	6.3991	5.9123
MSE	91.5109	103.1594	95.7053	77.9316
RMSE	9.5661	10.1567	9.7829	8.8279

4.2.2. *Determinants of fatalities and incidents*

After observing the previous results of airlines with larger profit margins expecting more accidents once an accident happens, we conducted two additional estimations. On the one hand, in order to measure the severity of the accidents, we estimate the number of fatalities conditioned on having an accident. On the other, we estimated the number of incidents which, by definition, are less severe events than accidents. Table 6 shows the results for both the Poisson and the Negative Binomial estimations.

For the case of fatalities, our results show that companies with larger levels of profit margins have a smaller number of expected fatalities, which means that their accidents are less severe. In this case, the overdispersion has clear consequences on the estimation results. As the test of $\delta = 0$ and the BIC criteria show that the Negative Binomial is preferred for this case, using a Poisson regression could yield a biased parameter estimation and underestimate standard error, leading to invalid conclusions. In this sense, and under the Negative Binomial model, costs per flight, distance, departures and technological progress are variables that significantly explain the expected number of fatalities, while maintenance cost is not significant. Regarding LCC variable, due to the lack of any fatal accident in the sample, is omitted. Finally, the 11-S dummy shows a significant coefficient.

Regarding incidents, the models show that profit margins are not significant for explaining the expected number. However, with the exception of the dummy variables, all the explanatory variables are significant for the expected number of incidents, with technological progress being the only factor with a negative parameter. Similarly to the number of accidents and fatalities, the likelihood ratio test and the BIC criterion show that the Negative Binomial model is preferred.

5. Discussion

In this study, which has been designed to re-analyze the link between safety and profitability, we identified several important issues that need to be discussed. Due to the existence of over-dispersion, all the comments in this discussion refer to the results of the estimations based on Negative Binomial distributions.

5.1. Zero-inflated model

The zero-inflated models are used in cases where the number of zeros greatly exceeds the number of positive cases. In the case of air transport where the zeros outperform any other number of accidents, this model is necessary. After checking the results of the Vuong test and the BIC criterion, our results confirm that this model is preferred over the traditional models used in the literature. Moreover, the zero-inflated model helps us understand the mechanism behind the effects of the variables on the expected number of accidents, where the common variables in the literature - such as departures - can help explain the probability of having an accident but not the expected number of accidents. Additionally, it can help to explain the counterintuitive results of having a positive parameter on profit margins without using the zero-inflated specification.

5.2. Effects on count variables

5.2.1. One-lagged profit margin

While classic literature, such as Rose (1990) and Raghavan and Rhoades (2005), showed an inverse relationship between accidents and profitability, it should be noted that these papers used data starting in the 50s. Thus, more recent papers such as Fardnia et al. (2020) found out a positive link between expected number of accidents and profitability. This counterintuitive effect is also found in our results. Nevertheless, the use of zero-inflated model can help to disentangle the mechanism behind it. Firstly, in relation to accidents, it shows a positive sign in the excess of zeros' model. This means that those companies with a larger profit margin have a lower probability of having an accident. However, as the coefficient for the number of accidents is positive, it means that after having an accident, the total number of expected accidents in a period can be higher for those companies with larger profit margin. It could be positing to think that after an accident, the company enhances safety protocols, lowering accident likelihood. Nevertheless, while having an accident is a rare event, our results show that the even rarer occurrence of having more than one accident, which only happens in 8% of the observations with accidents, is more likely in companies with higher profit margins.

Table 7 shows the expected number of accidents ($E[\widetilde{y}]$) under the ZINB estimation considering the company quartiles listed by the size of their profit margins. N represents the number of observations and s.d. is the standard deviation. The expected number of accidents is higher for medium-high and medium-low profit margins. However, high and low profit margins correlate with a lower expected number of accidents. Fig. 1 illustrates this relationship for each of the airlines by representing the quartiles with dashed lines. On the Y-axis, the figure represents the average number of expected accidents of a particular airline for the whole analytical period (which is positive or zero), while on the X-axis the average profit margin (which can be negative) for the overall period is represented. This means that dots on the left represent less profitable companies and dots on the right represent more profitable companies. On average, there is a growing relationship between profits and number of companies with accidents, as seen in the grey regression line.

To analyze the severity of those accidents, additional regressions were run over fatalities and incidents. The results, showed in Table 6, display that those companies with higher profit margins have a lower expected number of fatalities if they have an accident. This means that those companies' accidents are less severe. On the other hand, results

Table 6
Maximum likelihood estimates for passenger airlines fatalities and incidents and standard panel count data models with fixed-effects (period 1991–2018).

	Fatalities		Incidents	
	Poisson	NB	Poisson	NB
Profit margin$_{t-1}$	−3.1461***	−3.2104***	0.0240	0.0420
	[0.759]	[0.762]	[0.165]	[0.203]
Cost flight$_{t-1}$	−10.337***	−9.9956***	0.1716***	0.1672***
	[1.539]	[1.505]	[0.038]	[0.046]
Maintenance cost$_{t-1}$	−0.6023	−0.4287	0.0003**	0.0003**
	[0.499]	[0.633]	[0.000]	[0.000]
log Average distance	4.9028***	4.8156***	0.7213***	0.6954***
	[0.854]	[0.794]	[0.095]	[0.117]
log Performed departures	−4.8390***	−5.3589***	0.6754***	0.6359***
	[0.492]	[0.335]	[0.047]	[0.056]
Technological progress	−0.3448***	−0.3225***	−0.0943***	−0.937***
	[0.034]	[0.028]	[0.003]	[0.004]
LCC			17.1815	12.5138
			[7288.375]	[644.571]
11-S	7.1012***	6.8254***	0.1048	0.1991
	[0.462]	[0.748]	[0.108]	[0.143]
δ		8.0868***		0.260***
		[2.807]		[0.026]
Fixed-company effects	YES	YES	YES	YES
Fixed-time effects	YES	YES	YES	YES
Observations	372	372	4357	4357
Log likelihood	−499.74	−490.25	−4043.45	−3908.80
BIC	1289.50	1265.01	8639.93	8546.57

Standard errors in brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Expected number of accidents according to the profit margins under ZINB model.

Company	N	$E[\widetilde{y}]$	s.d.	Min	Max
High profit margins	1070	0.0807	0.1236	0	0.6222
Medium-High profit margins	1097	0.2118	0.1918	0	1.1551
Medium-Low profit margins	1077	0.1999	0.1981	0	1.1569
Low profit margins	1111	0.0456	0.0657	0	0.3028

about incidents indicate that there is no relationship between profit margins and the number of incidents.

5.2.2. Distance

The results show that distance is not important in explaining accidents. It seems that accidents are more related to landing and takeoff operations. Regarding fatalities, once the accident occurs, the distance traveled affects the number of deaths. This can be explained because larger airplanes are usually the ones that perform the longest routes. Finally, as the distance increases, the expected number of incidents increases.

5.2.3. Departures

As expected, this control variable is negative and significant in explaining the excess of zeros, meaning that the higher the number of departures, the greater the probability of having an accident. However, this variable does not show significance explaining the number of accidents. Regarding fatalities and incidents, a high number of departures decreases the fatalities but increases the expected number of incidents.

5.2.4. Normalized cost per flight

The variable seems to be significant in explaining the probability of having an accident. In this sense, those companies with a normalized cost per flight higher than the average

have a greater probability of having an accident. However, the

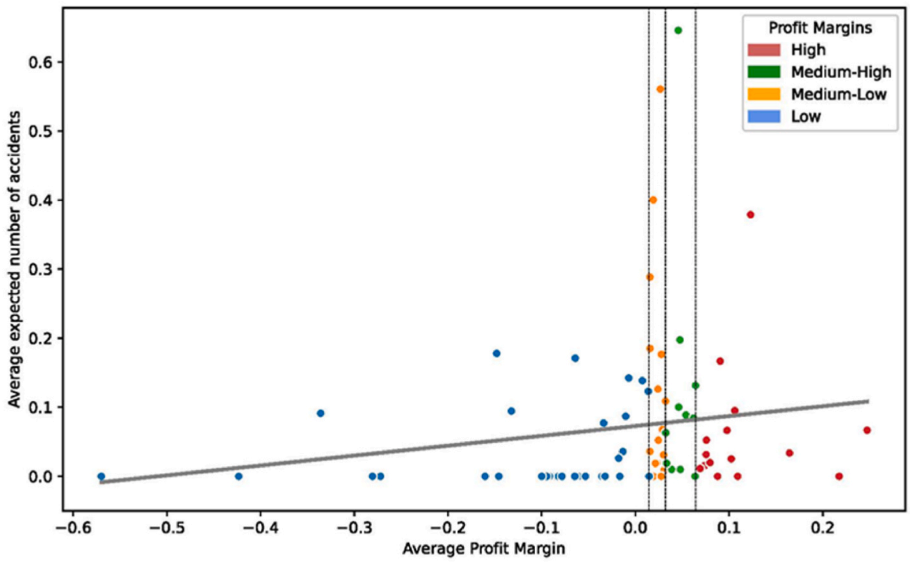

Fig. 1. The relationship between the profit margin per company and the expected number of accidents under ZINB model (period 1991–2018).

variable does not show significance to explain the expected number of accidents. Once an accident happens, the cost per flight is significant in explaining the fatalities: it is expected that companies with higher costs will have less number of fatalities. Finally, companies that show higher costs in relation to the average, expect to experience a higher number of incidents.

6. Conclusions

Our paper provides new evidence about the relationship between profits and safety by updating previous studies, such as that of Rose (1990).

On the one hand, it estimates not only the impact of profitability on the number of accidents, which is the most common aim in the literature, but also on fatalities and incidents. On the other, this study considers the statistical nature of accidents, fatalities or incidents, something that the relevant literature has not done so far. All of them are count variables with a lot of variability in relation to their mean (overdispersion). Furthermore, a plane crash is a rare event, so the database contains a large proportion of zeros. Therefore, this paper contributes to the empirical literature on the relationship between profitability and safety using a model that accounts for over-dispersion and excess-zeros in a count data panel framework. The model the paper proposes is the zero-inflated Negative Binomial, which has proved to better fit over-dispersed and zero-inflated data.

Estimation results show that the relationship between profits and safety has to be carefully analyzed due to the infrequency of accidents. The main results show that the companies with higher profit margins and lower costs per flight are the least likely to have an accident. While accidents represent a huge cost for airlines and they make great efforts to avoid them, it seems that airlines experiencing hard times can relax their safety protocols, thereby increasing the likelihood of a fatal event. However, once the event occurs, companies with higher profits are expected to have more accidents. There is empirical sufficiency to conclude that there are companies with large profits that suffered more than one accident in the periods analyzed. Nevertheless, regarding fatalities, these profitable companies are expected to have less severe accidents.

In relation to operational variables, first, there does not seem to be any relationship between the average distance of the flight and the expected rate of accidents. Distance positively affects the expected number of fatalities and incidents. Second, as expected, the number of departures positively influences the likelihood of the accident and the number of incidents, and negatively, the number of fatalities.

In sum, this paper provides a number of insights that might prove useful for researchers and policy makers. Firstly, from the policy perspective, regulators should focus on companies based on their profitability. As profitability is associated with a lower likelihood of accidents, severity is associated with poor economic performance. Regulators should ensure that airlines do not compromise safety in pursuit of higher profits. Conducting regular audits of airlines to verify compliance with safety regulations and ensuring appropriate precautions are being taken, or implementing higher penalties for airlines that fail to comply with safety regulations, including significant fines and even the revocation of operating licenses, are recommended measures to help increase safety. If the aim is to reduce the probability of an accident occurring, these measures should focus more on airlines with low profits. However, once a company has experienced an accident, the regulator must closely monitor that company, especially if it has high profits. It is possible that the company is achieving these profits at the expense of safety. Secondly, the presence of over-dispersion should be considered when analyzing the relationship between profitability and safety. Failure to account for over-dispersion can result in serious underestimation of standard errors and misleading inference for regression parameters.

Declaration of interest

none.

CRediT authorship contribution statement

Ubay Pérez-Granja: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **José María Pérez-Sánchez:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Jorge V. Pérez-Rodríguez:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization.

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