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Economic pressures on airlines' safety performance

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ABSTRACT

We investigate if general economic conditions influence aviation safety across the whole sector. Specifically, the study explores the relationship among aviation accidents and incidents for Part 121 US commercial airlines with fuel prices, stock market volatility, industrial production growth, and treasury bill rates. Our findings suggest that most of the variables under consideration exhibit a strong association with airline safety. Importantly, we examine two plausible channels that may explain these results; managerial decisions and the effect on "human factor". Analysis of airline financial data, health, and safety violations, along with airline employee satisfaction levels, suggests that it is more likely that the economy influences aviation safety through managerial decisions. This study confirms theoretical predictions about reductions on firms' quality standards in periods of financial stress and liquidity constraints. The findings of the study have important implications for regulators and other stakeholders.

1. Introduction

Theoretical considerations predict that, in response to financial pressures, firms to achieve their short-term goals may trade-off the quality of their products (Maksimovic and Titman, 1991; Golbe, 1988; Dionne et al., 1997). Such economic pressures could also result to safety levels deterioration. Past airlines' safety performance influences travellers decisions (Koo et al., 2019; Beck et al., 2018) but still potential ramifications borne from airlines when an accident occurs, are significantly smaller than the social cost induced (Borenstein and Zimmerman, 1988). The fact that the cost borne as a result of an airline accidents is not so severe, coupled with the low probability of an accident to happen, provide managers with a degree of freedom regarding the choice of a firm's safety standards (Dionne et al., 1997).

Previous literature, captures the effect of firm level pressures on individual airlines' accident records (Rose, 1990; Noronha and Singal, 2004; Raghavan and Rhoades, 2005). When pressures are imposed from critical cost components, it is possible that to reach the desirable profitability levels, firms to decide to invest less in other cost components, such as labour or maintenance. An after-effect of such decisions could be the deterioration of the safety standards. Several media articles entertain the idea that soaring fuel prices may put pressures on airline managers to impose strict cost efficiency policies that can adversely affect safety. The official industry view on that is adamant with the former IATA chief executive officer Tony Tyler stating that: "No airline will risk the safety of their passengers, crew and aircraft for the sake of fuel savings" (FT, 18/7/14). Although concerns are expressed by the media, industry and regulators about the link between airline profitability and safety (see, for example, the extensive account by Fraher, 2014), no empirical study has yet to examine whether fuel prices or other pressures coming from the general economy are linked to aviation safety.

This study addresses this gap and contributes to the literature extending previous research efforts that considers the effect of firm-level pressures on airline safety. It is known that financial problems of individual airlines are associated with higher accident rates (Rose, 1990; Noronha and Singal, 2004; Raghavan and Rhoades, 2005; Lin and Chang, 2008). The mechanisms explaining that relationship are also well established (O'Riordan et al., 1987; Golbe, 1988; Maksimovic and Titman, 1991; Dionne et al., 1997). At this study, instead of focusing on the drivers of accidents for a particular airline, our experimental design focuses on systematic risk factors that are related to the whole economy and, thus, are expected to affect the whole aviation sector. To this end, we explore the impact of fuel cost, a major operating cost component for airlines, on aviation safety. In addition, we examine the effect of indicators of the general economic environment and investors' uncertainty captured by the industrial production index, the 3-month Treasury bill rates, and the volatility index. Finally, we consider the market structure of the airline industry for the studied period measuring the Herfindahl–Hirschman index and we evaluate the effect of market concentration on the volume of airline mishaps.

The methodological design of the study addresses several limitations found in previous studies. In particular, analysis for the whole sector

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provides opportunities for improved statistical analysis with a larger dataset. Most importantly, it allows for higher frequency data as we can analyse safety at a monthly level. Firm level analysis that focus on firm financial performance indicators, due to data unavailability, can only be performed on quarterly basis. We can also extend the research about the effect of market consolidation and competition on safety. Existing approaches are event-studies based on a single point in time (e.g., deregulation). In this study we evaluate how monthly changes in market competition can influence safety over a long period of time. Finally, our broader perspective allows us to analyse beyond the financial problems of airlines and their effects. This is desirable as airlines outsource a significant part of their operations, such as maintenance and logistics, which affects safety (Quinlan et al., 2013). In this way, the link between safety and the financial conditions of an individual airline is less clear.

Our findings indicate that airline safety in the US is affected by general economic conditions. Increases in fuel prices, short-term T-bill rates, equity market volatility and past accident levels have a negative impact on the overall industry safety record. Then, we move a step forward by examining the channels that explain the observed effects. We assume and examine two plausible explanations for the revealed effects. One explanation is that firms decide to adjust the quality of their services to satisfy short-term goals (Golbe, 1988; Maksimovic and Titman, 1991; Dionne et al., 1997; Phillips and Sertsios, 2013). Firms under financial consideration and short-termism may take harsh decisions under the lens of shareholder value maximization (Fassin, 2005). An alternative explanation is that adverse economic conditions may impact aviation safety through their effect on "human factor". Human errors are considered as the primary source of aviation accidents accounting for 80 percent of mishaps (e.g., see Chang and Wang, 2010; Shappell and Wiegmann, 1996). This is in line with the literature that explores how the economy affects employees. Economic downturns are associated with increases in the levels of stress at work due to, for example, rising job insecurity, unemployment, underemployment and distrust towards the enterprise (e.g., see European Agency for Safety and Health at Work, 2009). Employee stress can lead to absenteeism, high staff turnover, disciplinary problems, reduced productivity, accidents, errors (e.g., see European Agency for Safety and Health at Work, 2014). For example, stressed employees are twice as likely to take repeated absence and are more likely to be involved in accidents (Kalia, 2002). Considering that, we explore if our findings can be explained through managerial decisions or the effect of economic conditions on the "human factor". First, we examine the effect of our economic variables on the financial performance of airlines. In the absence of significant relationship of the variables of interest with key firm financial indicators, managers should not have an incentive to react to economic conditions with decisions that could have an effect on safety. Second, we investigate if the effect of the economy on safety is mediated by proxies for management decisions and human factors. To this end, we employ an Instrumental variable regression model using health and safety violations as a proxy of managerial decisions and airline employee satisfaction shared through online reviews as a proxy of the human factor. Our analysis suggests that the results are explained through the managerial channel. Overall, we suggest that economic factors that signpost hazardous periods are of particular importance for regulatory bodies, insurance companies, and other stakeholders.

The rest of the study is structured as following: Section 2 contains related literature and the theoretical framework. Section 3 describes the data and the methodology with the empirical results reported in Section 4 while we conclude with a general discussion and the implications of the study in Section 5.

2. Related literature

Airline safety is characterized by asymmetries in information where service-providers know the quality of their product, though for the rest of the stakeholders (passengers, insurance companies etc.) this is not observable until the time an accident occurs. Safety performance is the result of investments undertaken from firms to yield a better return over time. This yield could take the form of lower insurance premia, lower accidents and liability costs or lower wages for the employees (Barnett et al., 1979). Several theoretical models exist for products with not ex-ante observable quality (Klein and Leffler, 1981; Allen, 1984; Shapiro, 1983). These models do not always predict lower quality. For example sellers' received premia may forestall reductions in quality or firms may overprovide quality to enter a new market. Myers (1977) introduces the underinvestment problem by arguing how the corporate debt can reduce the present market value of a company by rejecting good investments, at least to the point where their expected returns are less than the promised payments. The model proposed by Long and Malitz (1985) predicts that different investment choices gather different financial leverage. As a result, investments in intangible assets, which are difficult for the bondholder to monitor, do not have the same debt levels as investments in tangible assets. Investments in quality are often seen as investments in intangibles and there are not easily observable. Thus, it can be inferred that underinvestment due to debt financing is more discernible in quality-related activities.

Our work mainly draws on the theoretical model developed by Maksimovic and Titman (1991). This model assumes that consumers cannot directly observe the quality of the product which fits our research question as carriers' choices about safety standards are not easily observable from customers. According to Maksimovic and Titman (1991) firms have a degree of freedom about the level of provided quality. To reduce financial stress and/or bankruptcy risk, firms may follow a short-term maximization strategy by pricing a low-cost product as a high-cost one. Several studies support empirically the Maksimovic and Titman (1991) model (Phillips and Sertsios, 2013; Matsa, 2011). As safety is probably the major quality factor of the aviation industry and definitely an unobservable one, it is expected to be affected by firms' financial conditions. Rhoades and Waguespack (2000) confirm the relationship between quality and safety and report that passengers can deduce safety quality provided from carriers through the impression they have from service quality offered.

Aviation safety has been examined under different lens in extant literature. Scholars explore the financial impact of airline accidents for the involved firms. In this area studies evaluate the effect of accidents on airlines' or manufacturers' equity value. Barnett and Lofaso (1983) perform an empirical study for the effect of the DC-10 crash at Chicago in May 1979. They examine whether airlines that use the DC-10 type for their operations suffered a loss at their market share as a result of the accident. Surprisingly, they find that in the post-crash market the DC-10 exposed carriers achieved market share gains. In a subsequent study, Chalk (1986) investigates the effect of the same accident on the manufacturer's McDonnell Douglas equity and reports an estimated cumulative capital loss of $200 millions. Similarly, in a more recent study (Akyildirim et al., 2021) report a substantial income and leverage effects in the aftermath of a disaster for engine manufacturers. Chalk (1987) conducts a more extensive study in a sample of 76 US airline accidents (with at least one fatality) for the period 1966–1981. The study reveals a significant decrease in the market value in the case of manufacturer's liability. The reported decrease is equal to −3.7% of the equity value (an average loss of $21.32 millions). Mitchell and Maloney (1989) confirm significantly negative abnormal returns to the stock market price of airlines involved in fatal crashes, if there are implications that the accident is their blame. The abnormal returns reported are approximately 2.5% of the equity value and there are attributed to the "brand name effect" and to insurance premia adjustments. Bosch et al. (1998) confirm a switching effect consistent with the "brand name effect". Finally, the study of Borenstein and Zimmerman (1988) reports an average 1% loss of airlines' equity or $4.5 million in terms of market value, associated with a crash. These findings are quantitatively similar to the results of Chance and Ferris (1987) who report a 1.2%

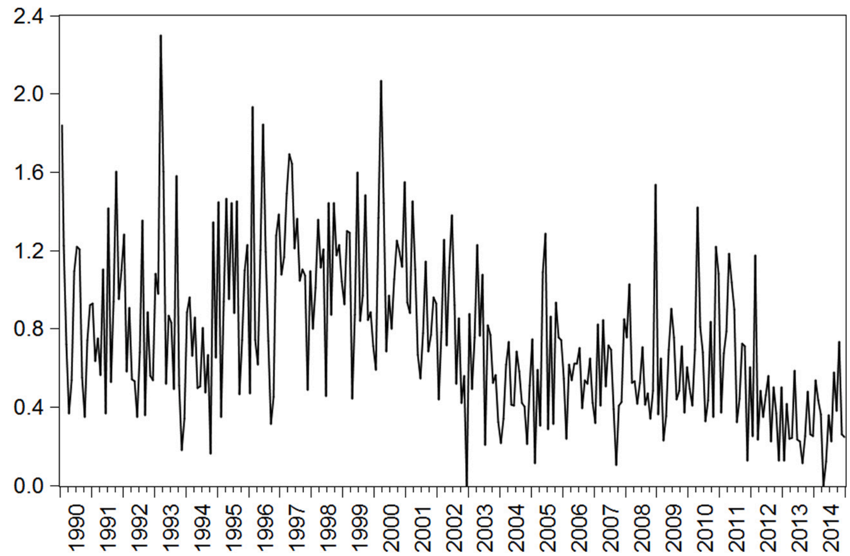

Fig. 1. Total aviation accidents and incidents per month in the US per 100,000 departures.

Table 1
Autoregressive negative binomial regression of accidents against economic variables.

$FUEL_{t-3}$	0.826**
	(0.301)
$TBILL_{t-3}$	0.108**
	(0.027)
VIX_{t-3}	0.233**
	(0.082)
IPI_{t-3}	0.704
	(4.224)
$ACCIDENTS_{t-1}$	0.150*
	(0.064)
DEP_t	1.039*
	(0.439)
AML_t	8.243**
	(3.092)
INT_t	−2.389*
	(1.169)
TIME	0.001
	(0.001)
HHI_t	−2.855
	(1.520)
Constant	0.600*
	(0.265)
Obs.	292
LL	−661.054

Standard errors (reported in parentheses) obtained by normal approximation.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

Table 2
Regression analysis of the impact the economy on safety regulation violations and employee satisfaction.

	OSH	REVIEWS
$FUEL_{t-3}$	1.287*	−0.082
	(0.619)	(0.119)
$TBILL_{t-3}$	0.114*	−0.016*
	(0.047)	(0.007)
VIX_{t-3}	−0.103	−0.093**
	(0.222)	(0.027)
IPI_{t-3}	−7.271	−3.227
	(10.436)	(1.690)
Constant	1.895**	1.226**
	(0.661)	(0.086)

HAC standard errors in parentheses.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

loss of shareholders wealth for carriers. The effects, though significant, are smaller than those reported to other sectors (e.g. pharmaceutical drug recalls). Evidently, the involved companies are penalized but the imposed "penalty" is not so severe (Noronha and Singal, 2004).

Previous research sheds also light to the link between profitability and safety. Rose (1990) reports a correlation of low profitability with higher accident records. A similar conclusion is deduced by Noronha and Singal (2004) using bonds ratings. In a more recent study, Madsen (2013) re-examines this topic by employing organizational risk taking theory and unveils that firms which are close to their profitability goals record higher accident rates than the airlines which are far above or far below their targets. To the best of our knowledge, the relationship between macro-economic factors and airline safety has not been directly investigated. The closest study is that of Stamolampros and Korfiatis (2019) who perform an analysis on macro-economic factors on airline service performance. In a related field in the literature, several studies investigate the impact of socio-economic factors to road accidents (Reinfurt et al., 1991; Wagenaar, 1984). These studies report a significant relationship between macroeconomic factors such as unemployment rate, economic growth and road accidents. Airline industry is particular sensitive to external shocks coming from the economic environment (Morrell, 2011; Fardnia et al., 2021). Therefore, it is sensible to examine the macro-economic environment as a determinant of accident rates.

In this study we examine the effect of four variables that proxy economic conditions: oil prices, interest rates, equity market volatility, and economic output. Our choice is based on the availability of monthly data and the knowledge derived from previous empirical studies (e.g., see Chen et al., 1986; Bloom, 2009). Data from IATA shows that fuel accounts for a large proportion of the total operating expenses (20%–30%). An increase in the price of this important cost component is likely to have a significant direct effect on the financial performance of all firms in the airline sector. In addition, fuel cost cannot be easily passed to customers (Carter et al., 2006b) while its volatility makes airlines susceptible to cash flow swings (Morrell and Swan, 2006). Under the pressure of soaring fuel costs, airlines may also adapt fuel efficiency policies that could result in minimal amounts of emergency reserves. Limited fuel levels narrow the choices of a pilot in following alternative routes if needed. Fuel prices may affect significantly airline safety through both the impact they have on the

Table 3
GMM Poisson regression of accidents against economic variables with safety regulation violations and employee satisfaction levels as instruments.

$FUEL_{t-3}$		1.248
		(0.874)
VIX_{t-3}	0.752	
	(0.386)	
IPI_{t-3}	16.205	−16.628
	(15.949)	(18.232)
OSH_t	0.521**	
	(0.141)	
$REVIEWS_t$		−0.938
		(0.874)
DEP_t	−0.767	−0.085
	(1.821)	(0.905)
AML_t	9.667	21.725*
	(7.843)	(8.517)
INT_t	−3.977	−4.789*
	(2.347)	(2.112)
TIME	0.002	−0.005
	(0.002)	(0.007)
HHI_t	−4.341	−3.838
	(3.433)	(2.500)
Constant	−1.914	2.647
	(1.720)	(1.963)
Obs.	286	80
Hansen's J χ^2	0.058	1.264
	(p = 0.809)	(p = 0.531)

Coefficients obtained using GMM estimation. Excluded instruments are *FUEL* and *TBILL* for OSH Violations and *TBILL* and *VIX* and *IPI* for employee satisfaction levels, respectively. Robust standard errors in parentheses.

*Denote significance at the 5% level.

**Denote significance at the 1% level.

firms but also more widely on the economy (e.g., see Hamilton, 2013). For that reasons we examine the following hypothesis:

H1: *Increases in fuel prices have a positive relationship with the number of airline accidents*

Debt pressures have a known negative relationship with investments and CSR activities (Moussu and Ohana, 2016). We use 3-month Treasury Bills (*TBILL*) as a proxy for US interest rates. T-Bills directly affect the interest payments and credit ratings of loans, bonds and leasing agreements for variable rate instruments and for raising new debt. Airlines are capital intensive and typically heavily leveraged firms. So, their profitability, credit ratings and cash-flows are particularly sensitive to interest rate variations. More generally, T-Bill rates contain information and expectations about the economy as a whole in terms of credit risk, liquidity, attitudes towards risk, exchange rates, stability and inflation. Therefore, we expect the following relationship:

H2: *Interest rates have a positive relationship with the number of airline accidents*

As a proxy for equity market volatility, we use the Chicago Board Options Exchange (CBOE) *VIX*. This is one of the most common measures of aggregate stock market risk in the US and is often used as a key barometer for investor uncertainty and sentiment. The *VIX* technically reflects expectations regarding the 30-day volatility from option market participants. The index is considered a forward-looking measure of the direction of the economy as it captures beliefs about the future. The association between the *VIX*, economic uncertainty and the business cycle is receiving increasing attention in the literature over recent years (e.g., see Bekaert and Hoerova, 2014). Higher levels of the *VIX* are associated with periods of stock market unrest and increased risk. This can lead to increasing difficulties related to costs of equity financing and liquidity. Therefore, we examine the following relationship:

H3: *Stock Market volatility has a positive relationship with the number of airline accidents*

We use the Industrial Production Index (*IPI*) as a proxy for economic output. Although more general measures do exist, such as the GDP, the *IPI* has the advantage of being sampled at monthly intervals which facilitates our empirical analysis. Decreases in *IPI* indicate contractions of the economy which in turn is closely related to consumption and transportation. Barnett (2010) connects GDP with airline safety in the cross-section of countries. The author reports a better safety record of wealthier countries compared to poorer countries. In our case, we study if better-off periods, in terms of production growth, are associated with fewer accidents within the same country. For that reasons we examine the following hypothesis:

H4: *Industrial production growth has a negative relationship with the number of airline accidents*

In parallel, we also examine the effect of varying levels of competition in the airline industry. This is motivated by the literature that examines if safety is affected by competitive pressures on firms or due to the entrance of inexperienced carriers into the market (Rose, 1989; Kanafani and Keeler, 1990; Foreman, 1993; Adrangi et al., 1997). A strand in the literature deals with the debate about the effects of deregulation and liberalization on safety standards. At the period of the deregulation there were several concerns that this event may deteriorate the safety standards due to competitive pressures on firms or due to the entrance of inexperienced carriers into the market (Rose, 1989). Adrangi et al. (1997) report no significant effect of deregulation on safety records. In imperfect markets, firms with leading position may exploit their power to reduce quality (Tirole, 1988). In their empirical study (Busso and Galiani, 2019) provide evidence that new entries in the market lead to significant improvement in service quality. Specifically, in airline industry (Chen and Gayle, 2019) report that mergers decrease product quality in markets where the merging firms were previously direct competitors.

3. Data and methodology

Airline safety is the outcome of safety investments and operating conditions (Rose, 1990). Safety investments encapsulate all the actions undertaken by air carriers in order to reduce the probability of an accident to occur (for example, maintenance expenses, new equipment, training). Operating conditions such as airports' safety infrastructure and weather conditions are exogenous variables that are not affected by firms' decisions. Evaluation of safety investments is rather difficult as there are not easily observable and/or distinguishable. Therefore, a reduced form model of safety performance is used where instead of the safety investments we focus on their observable output, meaning accidents and incidents records of air carriers. Thus, following previous literature we calculate the mishaps in order to infer the safety performance of airlines. Some scholars use the accidents (Golbe, 1983; Rose, 1990) while others use both incidents and accidents (Madsen, 2013). Accidents are quite rare to support statistical results while the incidents, according to previous scholars, have the disadvantage that are at carriers' discretion to be reported. In our research, we use both incidents and accidents as we consider incidents as near miss events or accidents that almost happened (Tinsley et al., 2012; Madsen et al., 2016; Gnoni and Saleh, 2017). As highlighted in Azadegan et al. (2019) near miss events can help on the identification of systemic issues. Most of the actions undertaken from carriers for safety appertain to loss prevention methods rather to loss control methods (Harrington et al., 1999). Loss control methods reduce the frequency of losses while loss reduction their severity. Given that, we are interested more in the frequency of mishaps rather in their severity. In our research, we consider only the serious incidents reported in the database of the National Transportation Safety Board (NTSB) and not incidents reported to the FAA Aviation Safety Information Analysis and Sharing (ASIAS) database where reporting could be more at the discretion of the carrier.

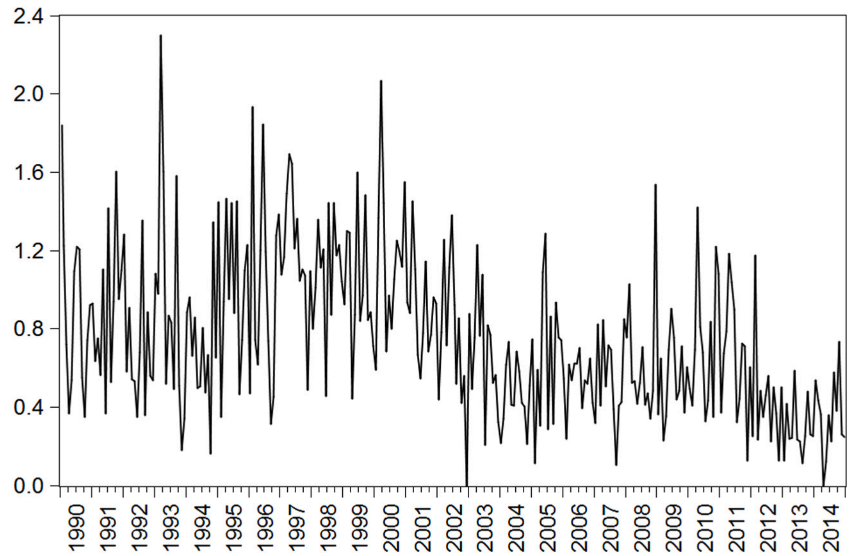

Fig. A.1. Total aviation accidents per month (Raw values).

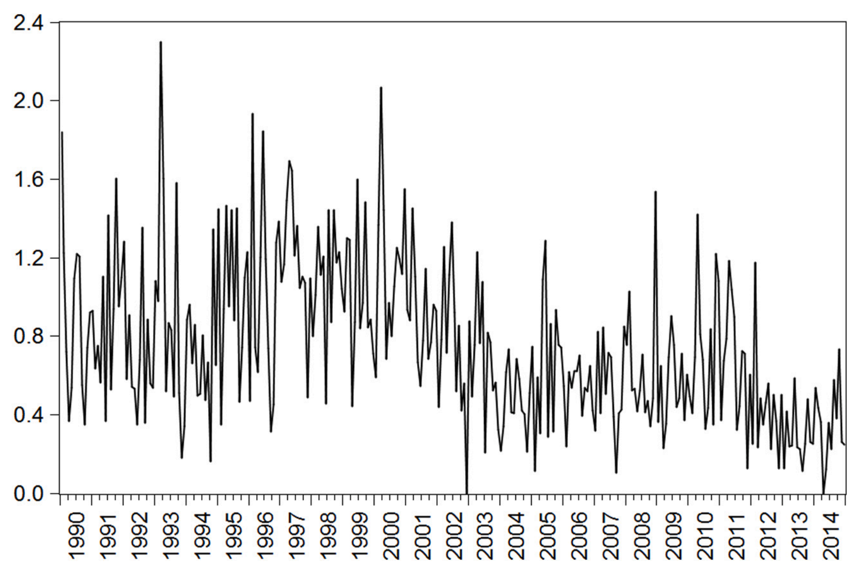

Fig. A.2. Total aviation incidents per month (Raw values).

Our data is retrieved from the NTSB open database and contains US air carriers classified as Part 121 for the period 1990 to 2014. We retrieve data for Part 121 carriers to be consistent with the previous literature and because this category has the biggest interest for passengers and secures an homogeneity in our sample. We retrieved both accident and incidents occurrences (fatal accidents, accidents, incidents). According to NTSB's classification an **accident** is defined as *"an occurrence associated with the operation of an aircraft which takes place between the time any person boards the aircraft with the intention of flight and all such persons have disembarked, and in which any person suffers death or serious injury, or in which the aircraft receives substantial damage"* while an **incident** is defined as *"an occurrence other than an accident, associated with the operation of an aircraft, which affects or could affect the safety of operations"*. Our depended variable is the number of accidents that occur during a month (denoted as *ACCIDENTS*). A graphical representation of the time series for the period is depicted in Fig. 1.

In line with the previous literature (eg., Raghavan and Rhoades, 2005; Borenstein, 2011) we control for the number of departures (*DEP*) and the average miles per flight (*AML*). Both are retrieved from the Department of Transportation (DOT), Bureau of Transportation Statistics (T-100 segment/All Carriers). Following Rose (1990), we measure also the fraction international to total departures (*INT*) to control for risk differences due to operations at foreign airports. In line with the existing literature to account for safety technological advancements, better maintenance, as well as for regulatory stringency which are expected to decrease the accident rate, a time trend variable is used on a monthly basis (*TIME*).

In order to measure oil prices and fuel costs (*FUEL*), we use monthly data on US Gulf Coast kerosene-type jet fuel spot prices drawn from the EIA US Energy Information Administration. Prices are "free on board" (FOB) and expressed in dollars per gallon. The *IPI* growth rate and the 3-month Treasury bills rates (*TBILL*) are retrieved from the FRED Federal Reserve Bank of St.Louis. Data for *VIX* are collected from the Thomson Reuters Datastream. We estimate the Herfindahl–Hirschman index (*HHI*) as a measure of the market concentration at monthly intervals using the T-100 segment report taking into account only domestic flights. HHI is considered as the benchmark tool of market concentration as it reflects, the number and dominance of firms in a market. For that purpose it is used by the antitrust authorities to assess the impact of merger on competition.

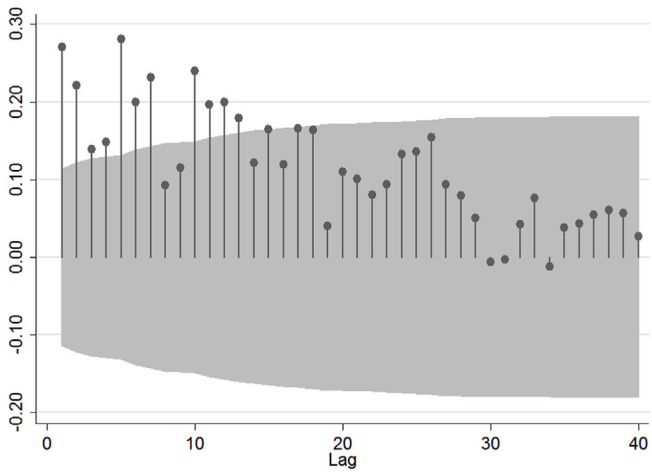

Fig. A.3. Autocorrelation of monthly accidents. Shaded area marks 95% Bartlett's confidence levels. The vertical axis denotes the autocorrelation values, and the horizontal axis denotes the lag ranging from 0 to 40. Values that are outside the shaded area show statistical significance.

Following the literature (Rose, 1990; Noronha and Singal, 2004; Wang et al., 2013; Madsen, 2013; Dionne et al., 1997; Raghavan and Rhoades, 2005; Golbe, 1983) and due to the nature of the dependent variable which is a count variable, the Poisson or negative binomial regression is a natural modelling choice. However, an analysis of autocorrelation suggests significant positive serial dependence in the first few lags of the occurrence series (see Fig. A.3). Beyond the effect that this may have on coefficient standard errors and inference, autocorrelation violates the key assumption of independence underlying standard count regression.

We deal with the issue of autocorrelation by introducing lagged accidents as an additional regressor. This addresses the problem of possible misspecification and allows us to test directly the possibility of serial persistence. A variety of count regression methods exist in the literature that allow autoregressive terms, including: serially correlated error models, hidden Markov models, discrete and integer valued ARMA type models (for a discussion see MacDonald and Zucchini, 1997; Kedem and Fokianos, 2005; Cameron and Trivedi, 2013). In our study we employ the model proposed by Fokianos et al. (2009), which has the following form:

$$g(\lambda_t) = \beta_0 + \sum_{k=1}^{p} \beta_k \tilde{g}(Y_{t-i_k}) + \sum_{l=1}^{q} \alpha_l g(\lambda_{t-j_l}) + \eta^T X_t \quad (1)$$

where $Y_t(t \in N)$ is the count time series and X_t is the vector of covariates. The conditional mean is described by a latent mean process λ_t such that $E(Y_t|F_{t-1}) = \lambda_t$ given that F_t is the history of a joint process $(Y_t, \lambda_t, X_{t+1} : t \in N)$ up to time t including the covariate information at time $t+1$. $g : \mathbb{R}^+ \to \mathbb{R}$ is a link function, $\tilde{g} : \mathbb{R}^+ \to \mathbb{R}$ a transformation function and the η^T vector is the effect of covariates. As we want to capture short range serial dependence, we employ a first order autoregressive term. The logarithmic function is used as a link function in order to allow for negative covariates. Estimation is done by a conditional quasi-likelihood approach based on the Poisson likelihood function for the negative binomial distribution.

4. Empirical analysis

A total of 1628 accidents occur over our sample period from June, 1990 to December, 2014. We exclude the accidents over 9/11 as they are related to terrorist attacks. The three worst months in terms of safety are May 2000 (15 accidents), April 2003 (8) and December 2008 (8) (see A.1 and A.2 for a graphical representation of the raw monthly values per category). For only 2 months out of 295 no accidents are recorded. The median number of accidents in our sample is 5 (Descriptive statistics of our variables appear in the Table A.1). On the basis of results from unit root tests, *HHI*, *FUEL*, *IPI*, *DEP*, *AML* and *INT* are transformed into differences in order to make them stationary. All variables, in levels or differences, are transformed into logarithms in order to facilitate their interpretation as elasticities.

4.1. Do economic conditions affect the number of aviation accidents?

All independent variables are entered with three lags (our analysis is based on monthly data so the lags refer to a period of 1 until 3 months back) in the test regression. Using a lagged structure is not uncommon in this literature as the effect of economic factors on safety could be gradual rather than concurrent (e.g., see, for example, Rose, 1990; Dionne et al., 1997). These studies have found that economic pressures coming from the previous quarter have an effect on airline safety. This may be explained by the findings of Borenstein (2011) who reports that *"When shocks do occur, there does not appear to be any barrier to capacity adjustment over three to six months in response"* (p.234). This could be related to managerial practices with respect to interim reports and hedging arrangements that take time to implement. This also agrees with the notion expressed by Madsen (2013) that any safety compromise derives from short-term aspirational goals. The aforementioned arguments and previous similar research designs lead us to selection of the three lags specification.

Results are summarized in Table 1. Most of the suggested relationships about our independent variables are supported. In particular, we find that increases in lagged fuel prices, interest rates and equity market volatility, all have a statistically significant adverse effect on safety. *IPI* and *HHI* are not significant although the latter has the expected sign and it is significant at 10% significance level. Control variables are in line with previous findings in the literature. Results also indicate a persistence in the accidents as the autoregressive term is significant.

For the robustness of the results we undertake several tests. Variance inflation factors (VIF) are well below the widely used threshold of 10 suggesting that multicollinearity is not likely to be a problem in our models (see Table A.2). Some applications of the negative binomial in the literature involve restricting the coefficient of the number of departures to unity. In this way it be treated as a normalization variable in order to obtain an accident rate rather than level (see Hardin et al., 2007). Although our unrestricted coefficient for the departures is close to one, the effect of posing a restriction during estimation has little effect (see Table A.3). Although the number of departures is the most popular normalization variable, the use of aggregate miles, gives similar results (see Table A.4). Estimation of the regression using alternative models, such as the Poisson or Gamma, allows very similar conclusions (see Fig. A.4 and Tables A.5 and A.6). In order to evaluate the suitability of our specification for the dependent variable, we apply the link test (Pregibon, 1980). This is also useful as a test that, conditional on the specification, the independent variables are incorrectly specified. The procedure, which is based on the explanatory power of the squared model predictions, gives insignificant results suggesting that model misspecification is not affecting our model (*p*-value is 0.841). Our results are also broadly robust with respect to the choice of the lag structure in the model. Although fuel price variations are statistically significant only with three lags, *VIX* and *TBILL* remain significant under alternative lag structures (see Table A.7).

4.2. Are firm decisions or human factors responsible for the effect of the economy on aviation safety?

At this point we want to examine if the observed results are driven by firm decisions or human factors. To shed light on this, we run two separate analyses. First, we examine the effect of our economic

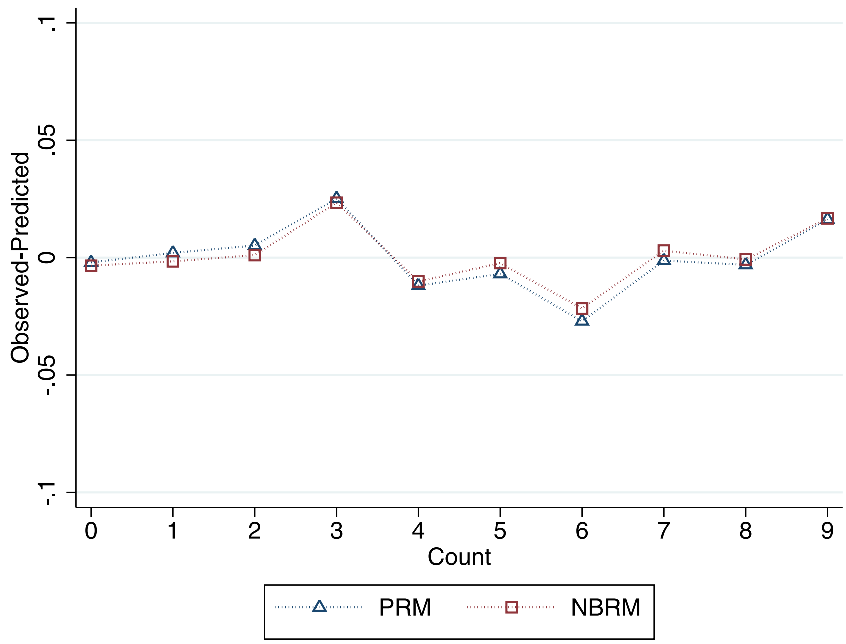

Fig. A.4. Graph of Poisson and negative binomial residuals.

Table A.1
Descriptive statistics.

	Dependent variable	Independent variables				Control variables			
	ACCIDENTS	*FUEL*	*TBILL*	*VIX*	*IPI*	*DEP*	*AML*	*INT*	*HHI*
Mean	5.50	1.36	3.03	19.96	88.61	7.58	708.56	0.08	1045.33
Median	5.00	0.82	3.22	18.31	93.47	7.51	710.99	0.08	1061.30
Max.	15.00	3.89	7.90	59.89	107.91	10.41	803.58	0.10	1389.35
Min.	0.00	0.30	0.01	10.42	62.37	4.73	634.67	0.05	793.44
S.D.	2.73	0.97	2.26	7.69	13.44	1.48	37.35	0.01	156.10

For the purposes of this table *DEP* is expressed per 100,000 departures.

Table A.2
Variance inflation factors (VIF).

	VIF	1/VIF
FUEL	1.02	0.98
TBILL	1.03	0.97
VIX	1.08	0.93
HHI	1.02	0.98
IPI	1.07	0.93
DEP	1.02	0.98
AML	2.21	0.45
INT	2.19	0.46
Mean VIF	1.33	

Variance inflation factors (VIF) are well below the widely used threshold of 10% suggesting that multicollinearity is not likely to be a problem in our models

Table A.3
Negative binomial regression with departures as offset variable for different lags (i).

	(i = 0)	(i = 1)	(i = 2)	(i = 3)
$FUEL_{t-i}$	−0.269	−0.633	−0.008	0.712*
	(0.264)	(0.340)	(0.360)	(0.330)
$TBILL_{t-i}$	0.051	0.057	0.064	0.065
	(0.035)	(0.035)	(0.034)	(0.034)
VIX_{t-i}	0.343**	0.297**	0.300**	0.302**
	(0.094)	(0.087)	(0.083)	(0.078)
IPI_{t-i}	5.837	1.768	5.458	1.860
	(4.431)	(4.018)	(4.484)	(4.362)
AML_t	7.483**	7.447**	7.568**	7.945**
	(2.410)	(2.434)	(2.486)	(2.516)
INT_t	−1.771	−2.082	−1.915	−2.096
	(1.089)	(1.131)	(1.194)	(1.187)
TIME	−0.002**	−0.002**	−0.002**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
HHI_t	−2.757*	−2.979*	−2.471	−2.738*
	(1.262)	(1.334)	(1.527)	(1.380)
DEP_t (offset)	1	1	1	1
Constant	−12.496**	−12.368**	−12.408**	−12.411**
	(0.324)	(0.304)	(0.269)	(0.253)
Obs.	295	294	293	292
LL	−676.457	−674.277	−674.136	−669.651

HAC standard errors in parentheses. Some applications of the negative binomial in the literature involve restricting the coefficient of the number of departures to unity. In this way it be treated as a normalization variable in order to obtain an accident rate rather than level (see Hardin et al, 2007, *Generalized Linear Models and Extensions*, Stata Press). Although our unrestricted coefficient for the departures is close to one, the effect of posing a restriction during estimation has little effect.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

variables on the financial performance of airlines. If no such relationship exists, then it is less likely that firms are reacting to economic conditions with decisions that have an effect on safety. Second, we investigate if the effect of the economy on safety is mediated by proxies for firm decisions and human factors.

4.3. The effect of the economy on the financial performance of airlines

We measure airline financial performance using variables related to the profitability (Return on Assets, EBITA Margin), liquidity (Levered Free Cash Flow Margin, Current Ratio, Quick Ratio) and solvency (Altman Z Score, number of bankruptcies). The number of bankruptcies is drawn from the U.S. Bankruptcies and Services Cessations list provided by the Airlines for America (A4 A) organization. The remaining variables are taken from the S&P Capital IQ database for 25 airlines (see Table A.8 for the list).[1]

[1] Although S&P Capital IQ report figures for 36 US. Airlines, we exclude those with very few observations. We also exclude those that are reported both separately and as a Group of airlines and retain only the Holding Group information in order to avoid duplicate records. Finally, we exclude Baltia Airlines from the sample as a non representative case.

Table A.4
Negative binomial regression with miles as offset variable for different lags (*i*).

	(*i* = 0)	(*i* = 1)	(*i* = 2)	(*i* = 3)
$FUEL_{t-i}$	−0.269	−0.631	0.012	0.732*
	(0.264)	(0.333)	(0.361)	(0.321)
$TBILL_{t-i}$	0.051	0.058	0.064*	0.064
	(0.034)	(0.034)	(0.033)	(0.033)
VIX_{t-i}	0.314**	0.272**	0.277**	0.280**
	(0.087)	(0.082)	(0.079)	(0.073)
IPI_{t-i}	5.686	1.382	5.002	1.307
	(4.577)	(3.907)	(4.364)	(4.399)
AML_t	6.827**	6.796**	6.902**	7.277**
	(2.358)	(2.370)	(2.451)	(2.454)
INT_t	−1.759	−2.062	−1.877	−2.063
	(1.074)	(1.117)	(1.179)	(1.165)
TIME	−0.003**	−0.003**	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
HHI_t	−2.909*	−3.122*	−2.634	−2.887*
	(1.276)	(1.347)	(1.530)	(1.385)
$MILES_t$ (offset)	1	1	1	1
Constant	−18.919**	−18.801**	−18.847**	−18.851**
	(0.308)	(0.294)	(0.264)	(0.244)
Obs.	295	294	293	292
LL	−673.697	−671.227	−671.034	−666.202

HAC standard errors in parentheses. An alternative normalization variable instead of the number of departures is the aggregate miles. Although the number of departures is the most popular normalization variable, the use of aggregate miles, produces similar results.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

Table A.5
Poisson regression of accidents against economic variables for different lags (*i*).

	(*i* = 0)	(*i* = 1)	(*i* = 2)	(*i* = 3)
$FUEL_{t-i}$	−0.133	−0.532	0.064	0.852**
	(0.260)	(0.314)	(0.360)	(0.319)
$TBILL_{t-i}$	0.114**	0.121**	0.129**	0.127**
	(0.037)	(0.038)	(0.036)	(0.037)
VIX_{t-i}	0.312**	0.260**	0.262**	0.266**
	(0.086)	(0.082)	(0.078)	(0.074)
IPI_{t-i}	4.680	0.989	4.727	1.367
	(4.778)	(3.986)	(4.488)	(4.253)
DEP_t	0.941**	0.881**	0.931**	1.024**
	(0.284)	(0.281)	(0.284)	(0.306)
AML_t	7.885**	7.656**	7.854**	8.441**
	(2.430)	(2.428)	(2.508)	(2.505)
INT_t	−2.034	−2.228	−2.118	−2.406*
	(1.115)	(1.152)	(1.198)	(1.182)
TIME	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
HHI_t	−3.009*	−3.086*	−2.661	−2.957*
	(1.344)	(1.422)	(1.612)	(1.470)
Constant	0.644*	0.788**	0.748**	0.742**
	(0.306)	(0.293)	(0.261)	(0.243)
Obs.	295	294	293	292
LL	−675.110	−672.564	−671.110	−664.312

HAC standard errors in parentheses. Although, the equidispersion test suggest overdispersion we reproduce our result with Poisson regression and the results are similar.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

The data are sampled quarterly and are used as dependent variables in a panel regression that includes the economic variables used previously. On the basis of a Hausman test, a random effects specification is used in the panel regressions (fixed effects produce similar results). For the regression involving the number of bankruptcies we use a Poisson regression given that we are dealing with a discrete variable. In order to retain the same time delay, a single lag is adopted for the independent variables in all models. The results support the conclusion that adverse economic changes cause significant deterioration in the

Table A.6
Gamma regression of accidents against economic variables for different lags (*i*).

	(*i* = 0)	(*i* = 1)	(*i* = 2)	(*i* = 3)
$FUEL_{t-i}$	−0.152	−0.515	0.123	1.109**
	(0.300)	(0.366)	(0.342)	(0.346)
$TBILL_{t-i}$	0.111**	0.119**	0.125**	0.127**
	(0.036)	(0.035)	(0.034)	(0.034)
VIX_{t-i}	0.348**	0.290**	0.285**	0.306**
	(0.098)	(0.091)	(0.087)	(0.079)
IPI_{t-i}	4.276	0.680	4.456	2.341
	(4.554)	(4.510)	(4.439)	(3.779)
DEP_t	0.981**	0.876**	0.862**	0.935**
	(0.310)	(0.310)	(0.305)	(0.326)
AML_t	8.430**	8.054**	8.139**	8.937**
	(2.569)	(2.535)	(2.576)	(2.661)
INT_t	−2.252	−2.457*	−2.435	−2.901*
	(1.207)	(1.179)	(1.271)	(1.291)
TIME	0	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
HHI_t	−2.753*	−2.754*	−2.406	−2.663*
	(1.158)	(1.312)	(1.274)	(1.216)
Constant	0.557	0.707*	0.699**	0.642*
	(0.330)	(0.308)	(0.267)	(0.254)
Obs.	295	294	293	292
LL	−791.555	−788.697	−785.844	−781.585

HAC standard errors in parentheses. Employing Gamma regression does not alter the direction of our results.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

Table A.7
Negative binomial regression of accidents against economic variables for different lags (*i*).

	(*i* = 0)	(*i* = 1)	(*i* = 2)	(*i* = 3)
$FUEL_{t-i}$	−0.136	−0.535	0.070	0.872**
	(0.264)	(0.319)	(0.358)	(0.322)
$TBILL_{t-i}$	0.114**	0.121**	0.128**	0.127**
	(0.037)	(0.037)	(0.036)	(0.037)
VIX_{t-i}	0.315**	0.262**	0.264**	0.269**
	(0.087)	(0.082)	(0.079)	(0.075)
IPI_{t-i}	4.657	0.985	4.741	1.458
	(4.774)	(4.024)	(4.491)	(4.171)
DEP_t	0.944**	0.880**	0.925**	1.018**
	(0.285)	(0.283)	(0.285)	(0.307)
AML_t	7.920**	7.692**	7.879**	8.473**
	(2.436)	(2.430)	(2.505)	(2.511)
INT_t	−2.052	−2.253	−2.153	−2.442*
	(1.123)	(1.154)	(1.205)	(1.191)
TIME	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
HHI_t	−2.992*	−3.087*	−2.659	−2.930*
	(1.334)	(1.420)	(1.594)	(1.460)
Constant	0.636*	0.779**	0.743**	0.734**
	(0.308)	(0.294)	(0.261)	(0.244)
Obs.	295	294	293	292
LL	−674.262	−671.722	−670.172	−663.667

HAC standard errors in parentheses. In line with the literature, we employ a count regression to test our hypothesis that the number of accidents depends on economic conditions. Assuming a random occurrence of accidents, the Poisson regression is a natural modelling choice. However, the equidispersion test of Cameron and Trivedi (1990, 'Regression-based tests for overdispersion in the Poisson model', *Journal of Econometrics* 46(3), 347–364) suggests that our data are slightly over-dispersed. So, the baseline model is the negative binomial regression in order to avoid biases in standard errors. Estimation is done via the maximum likelihood method.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

financial performance of airlines (see Table A.9). Specifically, for all variables considered, increases in fuel prices have a negative effect on financial performance. Industrial production has also a significant effect in all but two models. The impact of interest rates and the *VIX* is less significant but correctly signed in all but one cases. The use of

Table A.8
Capital IQ Airlines' list.

AirTran Holdings LLC	JetBlue Airways Corporation
Alaska Air Group Inc	Mesa Air Group Inc
Allegiant Travel Company	Midwest Air Group Inc
American Airlines Group Inc	Northwest Airlines LLC
Comair Holdings LLC	Pinnacle Airlines Corp
Delta Air Lines Inc	Republic Airways Holdings Inc
ExpressJet Holdings Inc	SkyWest Inc
Frontier Airlines Holdings Inc	Southwest Airlines Co
Global Aviation Holdings Inc	Spirit Airlines Inc
Great Lakes Aviation Ltd	Trans World Airlines Inc
Gulfstream International Group Inc	United Continental Holdings Inc
Hawaiian Holdings Inc	US Airways Group Inc
	Virgin America Inc

Table A.9
Regression of financial ratios and bankruptcies against economic variables.

	$FUEL_{t-1}$	$TBILL_{t-1}$	VIX_{t-1}	IPI_{t-1}	*Constant*	Obs.
Return on assets	−0.100**	−0.000	0.006	1.008**	0.010	1287
	(0.027)	(0.003)	(0.014)	(0.316)	(0.048)	
EBITA margin	−0.098**	−0.003	−0.013	0.943*	0.088	1441
	(0.027)	(0.004)	(0.016)	(0.392)	(0.049)	
Levered free cash flow margin	−0.146**	−0.014**	−0.036	1.119**	0.088	1275
	(0.056)	(0.005)	(0.022)	(0.359)	(0.067)	
Current ratio	−0.087	−0.016**	−0.133**	0.337	1.558**	1346
	(0.056)	(0.006)	(0.031)	(0.552)	(0.133)	
Quick ratio	−0.130*	0.002	−0.124**	1.496*	1.222**	1346
	(0.062)	(0.005)	(0.029)	(0.626)	(0.110)	
Altman Z Score	−1.382**	0.046	−0.041	15.689**	1.853**	1329
	(0.494)	(0.039)	(0.198)	(3.269)	(0.564)	
Bankruptcies	2.283**	0.269	0.219	−21.985	−0.738	96
	(0.700)	(0.161)	(0.394)	(13.184)	(1.166)	

Clustered standard error on carrier level for panel regressions in parentheses. HAC standard errors in parentheses for bankruptcies regression.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

Table A.10
Control function approach regression with endogenous regressors of accidents against economic variables.

$FUEL_{t-3}$		1.666**
		(0.580)
VIX_{t-3}	0.651	
	(0.343)	
IPI_{t-3}	16.295	−26.870
	(14.374)	(39.096)
OSH_t	1.116*	
	(0.552)	
$REVIEWS_t$		−0.199
		(0.736)
DEP_t	−0.294	−0.239
	(1.422)	(0.853)
AML_t	13.612	16.858
	(7.202)	(9.152)
INT_t	−5.199	−4.396*
	(3.135)	(2.088)
TIME	0.003	−0.012*
	(0.002)	(0.005)
HHI_t	−7.741	−3.193*
	(5.245)	(1.351)
$OSHresid_t$	−1.168*	
	(0.553)	
$REVIEWSresid_t$		0.012
		(0.767)
Constant	−2.445	4.401**
	(2.067)	(1.346)
Obs.	286	80

Coefficients obtained using control function approach. Excluded instrument are *FUEL* and *TBILL* for OSH Violations and *TBILL* and *VIX* and *IPI* for employee satisfaction levels, respectively. *OSHresid* and *REVIEWSresid* are the residual variables included to control for endogeneity. Robust standard errors in parentheses.
*Denote significance at the 5% level.
**Denote significance at the 1% level.

alternative measures of financial ratios as a robustness check leads to similar results.

Under the efficient market hypothesis, investors instantly incorporate all the information in their decisions. Having this in mind, we also examine how airline stock prices react to changes in economic conditions. We employ a market model in order to account for the effect of the market portfolio, proxied by the SP500 index, which is augmented by adding variations in fuel prices. We do not use lags in fuel prices as under market efficiency information should be reflected instantly in stock prices. The effect of the remaining economic variables is already accounted for in our model: interest rates in the risk free rate, *VIX* in the beta coefficient, and, *IPI* in the market portfolio. As dependent variables, we use logarithmic returns for 15 airline stocks listed on the NYSE. All data are drawn from Thomson Reuters Datastream. The estimation is done in a panel regression using fixed effects on the basis of a Hausman test. In addition to a significant positive beta coefficient of 1.279 (s.e. 0.148) for the SP500, we find a significant negative coefficient of −0.120 (s.e. 0.053) associated with fuel price variations. Similar results are obtained if instead of individual airline stock prices we use the equally-dollar weighted NYSE ARCA Airline index (AXGAL) which tracks the price performance of selected local market stocks or ADRs of major U.S. and overseas airlines (fuel coefficient −0.172, s.e 0.085). Overall, the results confirm that fuel price shifts will have an adverse effect on airline financial performance.

4.4. Disentangling the effect of firm decisions and human factors

In order to understand how the economy affects aviation safety, we examine the mediating effect of two proxies for firm decisions and human factors, respectively. We first assess if each one of the proxies is significantly linked to our economic variables. We then include both proxies as instruments in our regression of aviation safety against economic variables and controls. This allows us to identify if safety is driven by firm decisions and/or human factors. As a proxy for firm decisions, we use the frequency of violations for occupational health and safety regulations reported for US airlines. This is a measure of safety decisions that can be attributed directly to firms. As Filer and Golbe (2003) characteristically argue, such violations provide a"more accurate representation of the firms underlying safety decisions than accidents, which represent safety decisions only with a very large stochastic element" (p.365). Data is drawn from the Occupational Safety and Health Administration website for the period 1990–2014 for establishments under the SIC code 4512 (Air Transportation, Scheduled). Our sample contains 2595 reports, after removing 153 cases where no inspection data exist. From the reports, we count the number of violations per month. As this is a function inspection intensity, which may vary over time, we employ as a dependent variable in our analysis the ratio of occupational health and safety violations to the total number of inspections (the relevant variable is denoted as *OSH*). As shown in Table 2, the results confirm that increases in fuel prices and interest rates are significantly associated with an increase in violations. This is direct evidence that the economy has a significant effect on firm decisions related to aviation safety.

In order to proxy human factors, we use a subjective measure of self-reported airline employee satisfaction. Data on airline employee satisfaction are drawn from the Glassdoor database. Employee online reviews from Glassdoor have recently receive considerable attention in academic literature as valid approximation of employee well being (e.g., Green et al., 2019; Stamolampros et al., 2019; Symitsi et al., 2018, 2021). Glassdoor offers a collection of employee satisfaction ratings and reviews of their employers. Employees are asked to grade on a Likert-scale their overall satisfaction along with their satisfaction in specific categories such as compensation and benefits, work life balance, etc. We collect reviews for US airlines and employees from May 2008, which is the earliest date available, and end up with 2718 reviews between 2008 and 2014. As employee satisfaction differs significantly between airlines, we demean each review by subtracting the average value for each airline. From the standardized reviews we calculate 80 monthly averages of employee overall satisfaction levels (denoted as *REVIEWS*). In line with the literature, the results in Table 2 suggest that economic downturns, as proxied by shifts in interest rates and rising stock market volatility are associated with a deterioration in employee satisfaction.

The next step is to see if managerial decisions and human factors mediate the effect of the economy on aviation accidents. In order to estimate this effect and deal with the possibility of endogeneity, we employ a nonlinear instrumental variable approach based on GMM/IV Poisson estimators (for a general treatment of these models, see Heckman and Robb, 1985; Mullahy, 1997; Cameron and Trivedi, 2013). Application of a 2SLS estimation in case of non linear models leads to inconsistent parameter estimates (Windmeijer and Santos Silva, 1997). We use as instruments the variables that are found to explain the health and safety violations and employee satisfaction levels, respectively. Violations are instrumented with *FUEL* and *TBILL*, while, employee reviews are instrumented with *TBILL*, *VIX* and *IPI*, respectively. The results in Table 3 show that after correcting for endogeneity and the effect of economic variables, only OSH violations have a significant positive effect on the volume of accidents. This supports the explanation that it is more managerial decisions rather than human factors that are driving our results. Similar results (see Table A.10) are obtained if an alternative control function approach is adopted (Heckman and Robb, 1985; Mullahy, 1997; Cameron and Trivedi, 2013).

5. Discussion

Extant literature explores how firms adjust the quality of their product under financial stress (Maksimovic and Titman, 1991). The investigation of such behaviour is more important when the quality of the product is associated with human safety. Previous literature explores the financial drivers of accidents for individual airlines (Rose, 1990; Noronha and Singal, 2004; Raghavan and Rhoades, 2005). However, the discussion about aviation safety revolves only around firm-level determinants. This paper extends previous work by considering, for the first time, macro and sector factors instead of firm specific. We investigate this by examining the main cost factor fuel cost, and indicators of the general economy.

Our results support that several variables have an association with the overall aviation safety record. Results show that safety deteriorates in response to increases in fuel prices, short-term interest rates, equity market volatility, and, past occurrence levels, respectively. We shed further light by exploring the causal mechanism that explain these relationships. Specifically, we test whether these effects are the result of managerial decisions or the effect of the economy on the “human factor”. Analysis of health and safety violations along with airline employee reviews, suggests that the economy influences aviation safety performance through management decisions.

We should highlight here that airline industry has a remarkable safety record. Airline carriers’ safety levels are higher than any other means of transportation (Savage, 2013). However, on the basis of a continuous improvement, several practical implication emerge from our findings. Regulatory bodies should intensify their quality controls during periods of fuel prices increases or under periods of uncertainty. There is significant variation in fuel hedging practices amongst airlines and disagreement about the financial value it creates for shareholders (Carter et al., 2006a,b; Sturm, 2009; Morrell and Swan, 2006; Lim and Hong, 2014). Our paper shows for that fuel price volatility has a cost for society and customers in terms of a deterioration in safety levels. The estimated coefficients from our models in Table 1, suggest that the effect is not trivial. For example, for a 10% shift in fuel prices, which occurs in 35 months or 12% of the time in our sample, we can expect an 8%–9% increase in the number of accidents. As the median number of accidents is 5, a 9% increase means almost one more accident every two months (or 0.45 every month). On the basis of our results, we propose that regulators and airlines consider introducing minimum levels of fuel hedging across the sector. Limiting the discretion of hedging policies is desirable as financial pressures are known to lead airlines to hedge less, or, not at all (Rampini et al., 2014).

The results have also implications for insurers. In particular, lack of consideration from insurers to take into account market factors could result to higher uncertainty in estimating the expected loss and consequently to the application of proper insurance premia. Higher uncertainty derives mostly from risk that is not eliminated by pooling arrangements (undiversifiable risk). The magnitude of risk reduction through pooling arrangements is undermined when losses are not independent but correlated (Harrington et al., 1999) with some scholars arguing that correlation is the missing information to realistic models for insurance losses (Meyers, 2007). Although the importance of such form of market risk is obvious to some lines of insurance (e.g. seismic zones provide a market risk for mortgage insurance) the effect of macro-economic factors to the expected loss functions in other areas is not considered.

Declaration of competing interest

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

Appendix

See Tables A.1–A.10 and Figs. A.1–A.4.

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