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Literature Review

Stochastic Modelling of Air Passenger Volume During the COVID-19 Pandemic and the Financial Impact on German Airports

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Abstract

The current COVID-19 pandemic has hit most sectors of the world and has led to many industries coming to a standstill. It has led to restrictions of movement and travel ban. As a result of these restrictions, transport sector especially in aviation has impacted badly. A scenario-based analysis of the impact of the pandemic on the earnings before interest, tax, depreciation, and amortization (EBITDA) for airport operators is presented. Several causal factors affecting the air traffic volume are considered, including travel restrictions, consumer confidence, lack of international cooperation, and economic situation of the aviation industry. Stochastic equations with the standard Wiener measure are applied for modelling the air passenger volume in a given time frame. Based on a correlation analysis, the dependence of the EBITDA on the air passenger volume is modelled. As an application, for the two largest German airports, Frankfurt and Munich, the EBITDA is projected for different scenarios.

Keywords: COVID-19, forecasting, air travel, airport, financial performance, JEL: C53, L93

Introduction

The global spread of the SARS-CoV-2 virus provoked ad hoc national response actions to reduce the risk of importation or reintroduction of the virus from high-transmission areas. In February 2020, many countries have imposed health measures that significantly interfere with international traffic, ranging from denial of entry of passengers, visa restrictions or quarantine for returning travellers. This led to a reduction of domestic and international volumes of air passenger traffic, initially from and to China [53] and shortly afterwards in the Asia-Pacific region [57]. Further extensive global transmission led to the WHO declaring SARS-CoV-2 as a pandemic on 11 March 2020. In a corresponding joint statement, ICAO and WHO emphasized the importance on cross-sector collaboration at the national level as well as for the need to coordinate between aviation and health authorities. The importance of intense international co-operation and coordination between governments and other agencies was also pointed out [58]. Then, by 13 March 2020, Europe reported more cases and deaths than the rest of the world combined, apart from the People's Republic of China. In response to health systems starting to become over-whelmed, governments and national authorities worldwide have taken drastic and ad hoc unilateral measures comprising denial entry of passengers, closing airports and harbours, and ban on national and international travel.

It is well known that air traffic is impacted on national and regional scale by shocks due to political instability, terrorism, and economic crises [13, 40]. Furthermore, air traffic and the inter-connected industry have shown

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a sensitivity on pandemic outbreaks at regional and global scale [56, 57]. Not surprisingly, therefore, the uncoordinated measures at the beginning of the pandemic not only led to restrictions of human mobility but caused a social and economic crisis on a global scale. International trade and tourism as well as the transport sector especially in aviation have been impacted badly. Due to significant decrease of air passenger demand the airlines grounded many aircraft [3] and tried to find alternate, quick and effective measures to be able to survive the ongoing worldwide crisis. In contrast to the airlines, airport operators do not have many options rather than to maintain their operations to facilitate remaining cargo flights, and passenger or charter flights. Over the last decade, airports could well rely on the fact that mobility at global scale has been rising at a pace faster than the global population growth [93]. However, with the current situation, airport operators are concerned about their financial strategy as airport operation is, in general, linked to high fixed and unavoidable costs. In response to the crisis, many of the airports have to take difficult decisions under uncertainty, e.g. by closing portions of infrastructure and reevaluating the airport capital expenditure to reduce the cost to a minimum. The changed market situation currently is leading to a paradigm shift in corporate management, from the classic revenue orientation towards a value and risk-oriented management based on economic parameters. This will require a thorough analysis of the airport's operations to analyse the overall risk position, to qualify risks and to determine capital requirements. Hence, there will be an increasing need for risk-based valuations and appropriate tools for strategic decision-making.

The standard approach for time series forecasts and projections regarding passenger traffic and financial reporting is based on historical data in order to calibrate a suitable mathematical model for a given scenario and then project the values for future years accordingly. Simple deterministic forecasting models that neglect the non-linearity and stochasticity of passenger numbers might not be appropriate for investigating the impact of effects of the COVID-19 pandemic and possible management actions on an airport's financial performance. In this paper, a simple forecasting model which is based on stochastic processes with Gaussian white noise as widely used in risk management and finance (see, e.g., [79]) is presented. The paper is organized as follows. Section 2 provides a literature overview. The different data sources used are presented in section 3. Section 4 gives a brief description of the stochastic forecasting model. A search of government and other websites providing data and the literature on analysing the impacts of COVID-19 has been undertaken to derive the scenarios examined. The scenarios and the underlying assumptions are explained in Section 5. In section 6 the model is applied to estimate the impact of the COVID-19 pandemic on the financial performance for the two largest German airports.

Literature review

Over past decades, a variety of models for forecasting the air traffic or air passenger demand has been developed, ranging from simple exponential smoothing to complex hierarchical models [10]. The models that are generally used can be roughly classified into causal economic models, time series models, and artificial intelligence models [10, 24, 108]. Economic models focus on the correlation between the demand of passengers and multiple variables, which describe the functional influence of economic changes on the traffic system. Commonly used economic models include for example bootstrap models [24], Granger causality testing [38], gravitational models [47], logistic regression models [41], regression models [1], and stochastic frontier analysis models [126]. Time series models use historical data and a modelled relationship between current and past data series in order to predict the evolution of the modelled system. In the past, time series models have frequently been used to forecast passenger demand. Models and modelling techniques include autoregressive integrated moving average (ARIMA) models [74], seasonal ARIMA models [112], exponential time series [99], grey models [118], GARCH [2], Holt-Winters models [48], Markov Chain Monte Carlo modelling [117], Markovian models [22], Monte Carlo simulation [80], seasonal adjustment Monte Carlo modelling [9], smoothing technique models [99], stochastic queueing [103], and system dynamics [107].

However, due to the non-linear and stochastic characteristic of passenger demand, the forecasting abilities of economic and time series approaches for practical use are limited. Therefore, sometimes other methodologies are being employed, such as artificial neural networks [84, 86], artificial neural networks with data decomposition [5], weighted similarity-based algorithms [109], and hybrid artificial intelligence models with kernel extreme learning machines [64], generalized regression neural networks [123], improved particle swarm optimization [122], or least square support vector machines [102]. Since it was first proposed by Bates & Granger [12] that combination of forecasts from different models can produce better forecasts than the models acting individually, combination forecasting models became also quite common [72]. A combination of methods and techniques can reduce the uncertainties associated with individual models leading to an increased forecast accuracy by exploiting the strengths of the models and techniques being applied. Therefore, during the past decade, hybrid forecasting models became increasingly important for practical applications [10, 64, 106, 122].

More recently, time series forecasting models which are based on stochastic diffusion processes have been proposed. These models are based on the assumption that the random variable to be considered can be represented as geometric

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Brownian motion, fat tails processes or a mean reverting processes (see, e.g., [16, 79, 104]). Brownian motion models have been used for forecasting long-term demand based on historical data for aircraft production planning [125]. As shown in [77], the number of air traffic passengers can be represented as a geometric Brownian motion process. Although the model is widely used in risk management and in the rating practice, it has so far only been used sporadically for forecasting the number of air passengers [7, 8]. Finally, a model was proposed to evaluate the benefits of the investment in a new airport with the number of passengers, and the cash flow per passenger both assumed to behave stochastically [91].

The estimation of the financial performance of airport operators can be based on the earnings before interest, tax, depreciation, and amortization (EBITDA). Despite being a non-GAAP performance measure, EBITDA is widespread used for valuation, debt contracting, and executive compensation (see, e.g., [6, 20, 96, 101]. However, EBITDA excludes various expenses such as interest payments, tax, depreciation of assets and ignores amortization often stemming from goodwill. Furthermore, there is broad consensus that the informative value regarding the profitability and cash-generating ability is rather limited [14, 50, 96]. Nevertheless, the EBITDA can provide an indication of whether the post-pandemic rebound in air transport demand is leading to a similar improvement in financial performance of airlines and airport operators [90]. The EBITDA has been used previously in time series forecasting models, for example in artificial neural network models [66, 88, 110] or stochastic big data forecasting models [82].

Data sources

In this section the different data sources used in this work are presented.

Air traffic data

The air traffic data used in this work contain consolidated monthly air traffic information on the number of passengers and commercial flights for the 22 German international airports with focus on the largest two German airports, Frankfurt and Munich. The processed data is provided by ADV Germany [4]. Furthermore, the global number of commercial flights is used which is obtained from Flightradar24 [37]. Although in this paper monthly data is used, it should be noted that daily data or real-time data can also be used where available. Due to the aggregation and reporting process the data from the ADV data source may slightly differ to the actual passenger count at the airports. The data covers the period from January 2001 to December 2020. The volume of air traffic passengers for Germany is shown in figure 1. Besides the seasonal effect, an overall increasing trend till end of 2019 followed by the break-down due to the SARS-CoV-2 crisis can be noticed. Furthermore, the sudden drop in passenger volume caused by the Eyjafjallajökull volcano eruption in 2010 can be seen (cf. [19]). In 2019, a total of about 248.1 million air traffic passengers was reported by Germany's international airports, ranging from just 153.5 thousand passengers up to 70.5 million passengers. The two largest airports in Germany, Frankfurt and Munich, accounted for about 70.5 million and 47.9 million air traffic passengers, respectively. This corresponded to a market share of 47.7 percent for Germany. When analysing the passenger data in the period from January 2007 to December 2019 a strong correlation between the Frankfurt and Munich airports regarding the volume of air traffic passengers is found as shown in figure 2. Furthermore, the volume of air traffic passengers of Frankfurt and Munich correlates nicely with the total volume of air traffic passengers for Germany. The correlation coefficient for Frankfurt international is found to be $R^2 = 0.9684$, while for Munich international a correlation coefficient of $R^2 = 0.9578$ is determined.

The strong correlation between the air passenger volume of the two airports and the strong correlation between the individual air passenger volume and the overall passenger volume for Germany suggests that forecasts for the two airports give an indication on how the overall volume of air traffic passengers in Germany might evolve, and vice versa.

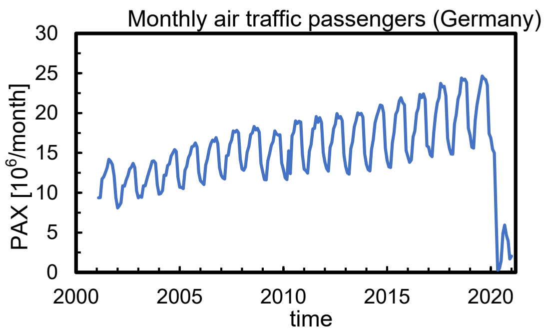

Figure 1: Aggregated volume of monthly air traffic passengers (PAX) for Germany from January 2001 to December 2020.

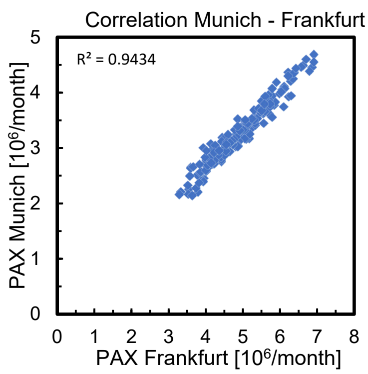

Figure 2. Correlation of the volume of monthly air traffic passengers (PAX) between Munich and Frankfurt airports based on data from January 2007 to December 2019.

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Financial reporting data

In order to estimate the impact of the COVID-19 pandemic on the airport's financial situation due to significant decrease of air passengers, available financial reporting data is used [39, 83]. By means of correlation analysis several balance sheet items can be identified which depend on the volume of air passengers. It is found that the EBITDA correlates well with the passenger volume. For example, for Frankfurt airport the correlation coefficient between EBITDA and the air passenger volume in the period January 2019 to September 2020 is found to be $R^2 = 0.9570$.

It should be mentioned that the data quality can be improved if the airport's internal balance sheet items are being used instead of the published reporting data. This is particularly valid for airports, where just annual reports but no interim releases are being published. However, for demonstrating the feasibility of the approach presented in this paper, the data quality should be sufficient.

Pandemic data and health situation data

In the course of the pandemic to date, it could be observed that control measures and government interventions against COVID-19 were mainly driven by the number of people seeking medical treatment, being hospitalized, receiving ICU treatment, or dying from or in connection with the disease. Therefore, trends in numbers of SARS-CoV-2 infections, deaths, and vaccinations must be considered for anticipating health and possible control measures to be taken by governments and national authorities impacting international air traffic and travel. It should be noted, however, that decision-making in a rapidly evolving pandemic is rather nuanced, depending on many causal factors [113] and may result in a wide range of hard to predict interventions varying over time [15]. The virus mutates rapidly [21, 81, 114]. Research shows that it can change in a way that makes it more contagious to humans [25, 51, 115].

The rapid increase of COVID-19 cases in England, of which a large proportion belonged to a new variant of the virus, almost immediately provoked uncoordinated flight and train bans by several EU States [35]. Under such circumstances the development of scenarios taking government measures into account is a difficult task and the resulting scenarios might be erroneous. Nevertheless, is seems plausible that strictness and timeline of health measures imposed in future is strongly linked to by the number of new infections and deaths, the number of hospitalizations, free ICU capacities, and vaccination coverage. The pandemic data required for development and adjustment of scenarios comprises consolidated monthly new infections and deaths through or in connection with the virus. The corresponding data used here is provided by JHU CSSE [29, 63] and RKI [94]. Data concerning the vaccination monitoring for Germany is provided by RKI [95].

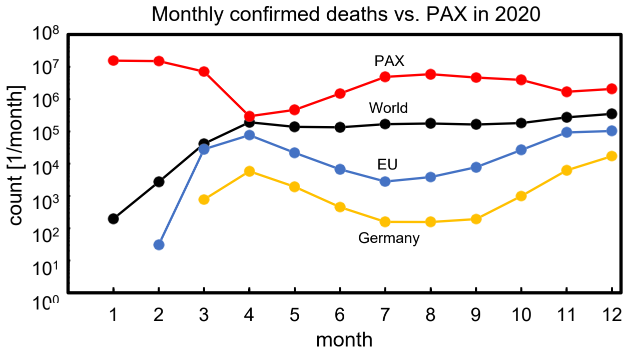

Figure 3: Number of monthly COVID-19 deaths in 2020 for the world, the EU, and Germany on a logarithmic scale. The volume of monthly air traffic passengers (PAX) for Germany in 2020 is plotted as dashed red line.

The monthly confirmed infections and reported deaths for the world, for the EU, for Germany, as well as the monthly reported air passengers for Germany in 2020 are shown in figure 3. The number of deaths in Europe and Germany increases as the number of air passengers decreases. Similarly, but somewhat less correlated, the monthly reported air passengers are decreasing with increasing number of new infections (figure 4). The data between the EU and Germany shows a nice correlation for both, number of deaths as well as number of new infections. Surprisingly, except for the early phase of the pandemic, there is no clear correlation between the pandemic data of the world and the air passengers in Germany. This suggests that the evolution of the number of air passengers in Germany is strongly coupled to national measures such as travel warnings, travel restrictions, quarantine, and lockdowns driven by the number of deaths in Germany and other European countries. Finally, one should note the rather good correlation between Germany and the EU. This holds for both, the number of infections as well as for the number of deaths, although Germany and other EU States imposed restrictive measures such as border closures, lockdowns etc. at different times and with different degree of restrictiveness.

Forecasting model

For the forecast of passenger volume, the historical data for the period January 2007 to December 2010 is decomposed into a periodic seasonal function calibrated on historical data, and a baseline function accounting for annual growth. For the periodic seasonal function, a low-order polynomial (of order 4 or 5) is used. This simplifies the calculations significantly, as the series $\Sigma\, nk$, where n,k are natural numbers, can be expressed as a polynomial of order $k + 1$. Hence, by fitting accumulated monthly air traffic passenger data over the period of a year to a $(k + 1)$-order polynomial, and taking differences on a daily base, the deduced data can be fitted to a k-order polynomial $f(x,t)$ that now describes the smoothed daily air passenger volume $x(t)$. Therefore, the evolution of

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$x(t)$ can be described by the following ordinary differential equation

$$\mathrm{d}x = f(x,t)\,\mathrm{d}t \quad \text{with } x(0) = x_0. \tag{1}$$

Now, the deterministic daily air passenger volume $x(t)$ will be described by the (integer-valued) random variable $X(t)$. For numerical solution, equation (1) is re-written by applying the forward Euler method for a small timestep Δt. By adding a noise term $g(x,t)$ describing stochastic fluctuations the following stochastic differential equation is obtained

$$X(t + \Delta t) = X(t) + f(X,t)\,\Delta t + g(x,t)\,\mathrm{d}W$$
$$\text{with } X(0) = x_0 \tag{2}$$

where $\mathrm{d}W$ is the so-called Gaussian (white) noise. The noise term needs to be modelled in accordance with the historical daily data, where available. Due to the lack of available daily data, here a constant estimate, $g(x,t) = \alpha x_0$, is used for simplicity. The numerical solution of the stochastic differential equation (2) gives sample paths for the stochastic evolution of the air passenger volume. For estimating variances, a sufficient large number of paths needs to be calculated. This can be done in a straight-forward manner by Monte Carlo techniques. Here, however, the stochastic air passenger volume is constructed by using Gaussian white noise. Hence, it is much more convenient to integrate the stochastic differential equation analytically by applying Itô's lemma and to compute the variance by using Itô isometry (see, e.g., [61, 62, 92, 111]).

In order to quantify the economic impact of the pandemic a functional relation between relevant financial reporting data and the air passenger volume can be used. A correlation analysis of the data used in this paper shows that the dependence of the EBITDA on the air passenger volume can sufficiently well described by using low-order polynomials. Thus, the EBITDA can be written as a functional of the stochastic air traffic passenger volume. Passenger-independent contributions to the EBITDA, for example due to earnings from air freight, can be accounted for by using a suitable linear combination of passenger-dependent and passenger-independent scaling functions of the EBITDA. This is particularly useful in the analysis of scenarios for developing passenger-independent business solutions that are expected to have a positive impact on the EBITDA, such as the impact of staffing strategies, infrastructure optimization strategies or reorganization measures.

Scenario background

The stochastic forecasting model does not take into account effects imposed by social human behavior, any SARS-CoV-2-driven economic impact or government decisions. Due to its global scale effects of the current COVID-19 pandemic differs to the ones of past crisis like the SARS-2003, MERS-2005 and others. Hence, experiences and findings of past crises can be transferred to the current situation to a rather limited extent only. For instance, crisis occurring in the past two decades caused declines in the global air passenger volume in the order of 10% or less [54, 57]. The avian flu outbreaks in 2005 and 2013 had even less impact on air transport and the aviation industry. Furthermore, for the more severe crises of the past air travel volume began to recover within 2-3 months and returned to pre-outbreak levels within 6-9 months [54, 56], following a so-called U-shaped recovery pattern. For the ongoing COVID-19 pandemic none of the above can be observed. Therefore, scenarios that try to quantify disruptions in air passenger volume need to be developed. These scenarios need to be combinable with the stochastic forecasting model and should account for air passenger options driven by political decision making, social interaction, media communication, the economic situation of the aviation and tourism sector, as well as the general evolution of the pandemic. Furthermore, the dependency of the issue of travel restrictions on the political decision-making under the conditions of a pandemic needs to be considered [71, 113].

In the literature, a variety of non-pharmaceutical measures taken by governments and authorities which are impacting the air passenger volume have been described. The assumptions which will be used in the scenarios in this paper are based on the synthesis of the literature taking into account current developments and trends over the course of the pandemic. It is assumed that the air passenger volume is affected by relevant non-pharmaceutical measures that are classified according to the following selection of key areas:

- travel situation
- consumer confidence
- international cooperation
- economic situation

The measures are further quantified by using the impact levels low, medium, high and very high. Then, the scenarios can be composed of the weighted contributions of the four key areas. The considered key areas, typical measures taken by governments and authorities and as well as an impact estimation are summarized in table 1.

Travel situation

One of the unique features of the ongoing COVID-19 crises that need to be considered in forecasting models is that due to the travel restrictions, flight bans, quarantines, lockdowns and social distancing measures enforced by governments, both supply and demand on air transport are affected on a global scale. By end of 2020 almost all countries over the world have introduced travel restrictions of some kind but the rules keep changing and differ, depending on the nationality of the traveler, place of residence, travel history or country of arrival. Moreover, imposed measures have influenced

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Table 1: Considered key areas used for scenario building together with relevant non-pharmaceutical measures and their possible impact on air passenger volume.

Key area	Measure	Impact level
1. Travel situation	1.1 Border closure	very high
	1.2 Suspend transportation	very high
	1.3 Accommodation and	very high
	tourism services shut- down	
	1.4 Travel restriction	
	1.5 Quarantine	high
	1.6 Travel warning	high
	1.7 PCR testing	high
	1.8 Masks & social	medium
	distancing	low
2. Consumer confidence	2.1 Media reporting	very high
	2.2 Lockdown	very high
	2.3 Changing rules and	very high
	heterogeneous rules	
	2.4 Non-transparent	high
	decision making	
3. International cooperation	3.1 Immediate unilateral	very high
	regulations and actions	
	3.2 Different quarantine	very high
	rules	
	3.3 Different immigration	high
	rules	
	3.4 Different criteria for	high
	risk area definition	
	3.5 Different passenger	low
	locator forms	
4. Economic situation	4.1 Grounded airplanes	very high
	4.2 Reduced demand	very high
	4.2 Reduced flight plans	high
	4.4 Short-time work	high
	4.5 Layoff of employees	high

public perception of safety. This has unprecedented impacted international air travel as restrictions that allow only *essential travel* suppress demand to a level where most routes can no longer be operated commercially. Flight and travel bans are being justified by governments as a measure to contain the spread of SARS-CoV-2, concerns that measures taken by some countries may not be efficient enough, and statistical data the number of new cases and on deaths. There is evidence that the effectiveness of travel restrictions and border closures on reducing the spread of SARS-CoV-2 is best early in the outbreak. However, restrictive measures become much less effective when implemented late [46, 75]. At present, there is limited evidence about the effectiveness of travel bans to minimize global emerging infection disease spread [32, 98]. Early detection, self-isolation, and household quarantine might likely be more effective than travel restriction at mitigating the pandemic [23, 70]. It was found that by September, the contribution of international travelers to most countries' COVID-19 case count had dropped significantly [97]. Thus, with respect to the epidemic dynamics travel restrictions might have some impact in countries with low SARS-CoV-2 incidence and large numbers of arrivals from other countries, or where epidemics are close to tipping points for exponential growth [97].

For Germany, aggregated data on the probable country of infection was reported in certain daily situation reports of the Robert Koch Institute [94]. Although the reports available to the public are not that stringent and detailed, an analysis for the period 27 July to 15 November reveals that the maximum contribution from international travel was about 53% end of August (week 34). Most infections were reported from travels to the Balkans with 2696 confirmed cases followed by travels to Turkey, Spain, Romania, and France, with 496, 296, 174, and 156 reported cases. Thereafter, as shown in figure 5 the weekly case count related to international travel was constantly decreasing to about 10% by end of September and to less than 1% by mid of November (week 46). It should be noted, however, due to a change in national testing strategy and the underlying national directives during summer more travelers were tested than before leading to an increased number of confirmed travel-related cases. This implies that the percentage values given above cannot be accurate but should rather be interpreted as a lower limit. This means that the vast majority of more than 99% of the new infections reported by mid of November should be of domestic origin. Furthermore, in summer, travel between Germany and the Balkans, and Germany and its neighbor states were carried out more likely by using cars and trains rather than aircraft. Despite the lack of accuracy, this data seems to support the assumption

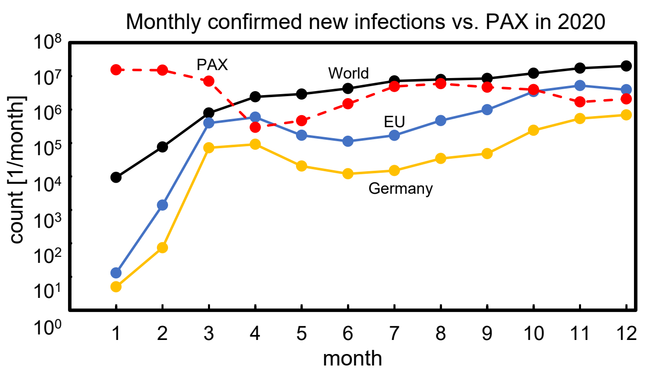

Figure 4: Number of monthly confirmed new COVID-19 infections in 2020 for the world, the EU, and Germany. The volume of monthly air traffic passengers (PAX) is for Germany in 2020 is plotted as dashed red line

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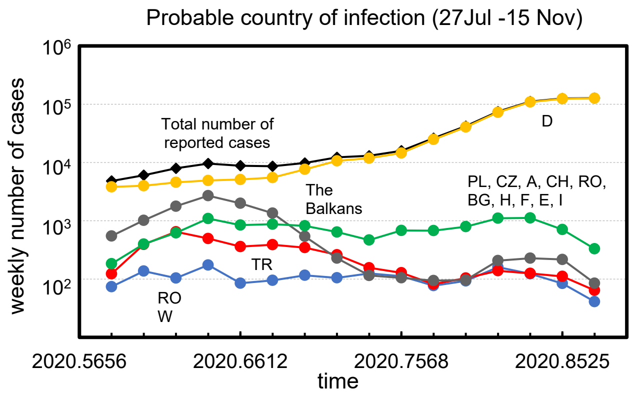

Figure 5: Weekly number of reported cases for Germany and probable countries of infection based on data reported by RKI. The data covers the holiday periods in summer and autumn from 27 July to 15 November 2020. The countries are: Austria (A), Bulgaria (BG), Switzerland (CH), Czech Republic (CZ), Germany (D), Spain (E), France (F), Hungary (H), Italy (I), Poland (PL), Romania (RO), Turkey (TR), the Balkans (Albania, Bosnia and Herzegovina, Croatia, Kosovo, North Macedonia, and Serbia), and the rest of the world (ROW).

that the contribution of international air passengers to the SARS-CoV-2 case count is rather low. Other research results also indicate that the risk of SARS-CoV-2 transmission on planes is rather low [52]. Although international travel drove introduction of the virus, in the U.S. domestic travelers rather than international visitors were found to be the source of the first wave of infections [26].

Consumer confidence

Previous findings suggest that even in cases where governments did not physically or legally prevent trade or travel, but rather imposed measures that influenced public perception of safety or did nothing to mitigate the fears of the public is affecting consumer confidence and, hence, travel [113]. This is also valid for the EU market. However, there is not much primary data available. In fact, individual choices of consumers were found to be far more important than legal restriction and seem tied to fears of infection [42]. However, factors such as flexible ticket booking and quarantine rules do not appear to be key drivers affecting travel decisions [44]. As noted by WHO, communication of factual information is essential to build trust in travel advice, increase compliance with health advice and prevent the spread of rumors and false information [120]. Hence, communication of information to the public through traditional media, social media and other channels about the potential risk of travel and the measures required to ensure safe travel including regular updates on changes in international travel can be identified as a key objective of COVID-19 preparedness and response [59, 120]. On the other hand, a government that discovers an outbreak and makes it public can expect to be the target of other States' trade and travel restrictions. Not surprisingly, then, States may not be eager to report outbreaks rapidly and transparently [121] which in turn negatively affects consumer confidence.

During pandemics public risk perception is affecting consumer confidence and people's willingness to adopt preventative public health behaviors [30]. Online news and social media in particular play an important role in the public risk perception and, hence, the public response to the current COVID-19 pandemic (see, e.g., [31]). It is known that exaggerated perceptions of risk can potentially undermine the adoption of protective health behaviors [73] and perception, whether correct or incorrect, often influences economic decision making [119]. The effect of public risk perception on travel decisions during the COVID-19 pandemic has already been observed (see, e.g., [11, 65, 67, 89]). The impact of non-pharmaceutical measures imposed by governments on the evolution of the air traffic passenger volume and the number of flights can be seen in figure 6 and figure 7. Border closures and travel restrictions account for the dramatic decline that can be seen from mid of March to June 2020 for both, the monthly air traffic passengers (figure 6), and the number of commercial flights (figure 7). For information, the data of 2019 are also shown. In figure 7, the right-hand side y-axis

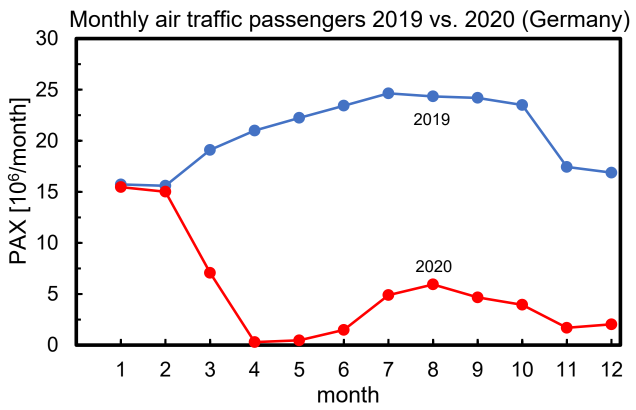

Figure 6: Monthly air traffic passengers for Germany in 2019 and 2020.

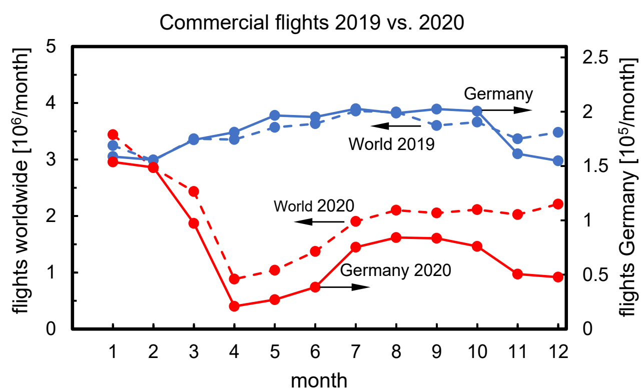

Figure 7: Monthly commercial flights worldwide and for Germany. Due to the scaling of the y-axis, the data is normalized to the 2019 level.

(for Germany) has been scaled so that the accumulated flights in 2019 are normalized to the accumulated worldwide commercial flights. The plot of the 2020 data shows that in relation to the worldwide data, the decline in the number of commercial flights is greater for Germany than that observed worldwide. With gradual lift of the travel restrictions and opening of borders, the number of flights and the number of air traffic passengers started to recover. In September, the number of air traffic passengers started to decline again, whereas the number of flights nearly remains on the same level as of August. This reduction in air passenger volume may be a result of the public risk perception due to a highly negatively polarized news worldwide [69]. This can be seen more clearly when comparing the ratios of monthly air traffic passengers to the number of commercial flights for Germany based on the data provided by ADV [4].

The results are presented in table 2. For the 2019 data the ratios from June to October differ only little. For the 2020 data, the ratios of September and October are smaller than the ones of July and August. The drop in November and December 2020 is again due to another lockdown in Germany and other EU Member States. The gap between summer 2019 and summer 2020 can be explained by a significant reduction of international traffic from/to the Americas and from/to North Africa [34]. In conclusion, the data available is supporting the assumption that consumer confidence is a key factor affecting pandemic-related traffic levels.

Table 2: Ratio of air traffic passengers (PAX) to the number of commercial flights for Germany (2019 vs. 2020) given per month.

Month	PAX / commercial flights	
	2019	2020
January	99.06	100.57
February	100.15	100.92
March	109.72	72.75
April	115.92	14.07
May	113.14	17.17
June	120.04	38.51
July	121.56	65
August	122.5	70.49
September	119.55	55.88
October	117.18	51.84
November	108.09	33.43
December	108.99	42.6

Lack of international coordination

Across the world the scope of travel and flight bans varies. For example, by presidential proclamations the United States suspended entry of non-U.S. citizens who were physically present within the People's Republic of China, Iran, European Schengen area, Ireland and United Kingdom, and Brazil during the 14-day period preceding their entry. At EU level, Member States have introduced temporary internal border controls and measures restricting free movement at some point during the pandemic. Although the EU has also worked to coordinate travel restrictions, the implemented rules and measures differ and keep changing as the pandemic progresses. Some States introduced flight bans for a few specific countries that have a higher rate of SARS-CoV-2 cases or where new mutations were identified, while others require travelers to quarantine (with differing periods of quarantine being required) or to present a negative polymerase chain reaction (PCR) test on arrival with differing maximum validity periods. Member States also use different national traveler locator forms, criteria for defining risk areas and requirements regarding the use of masks [36].

All this has made controls at airports difficult, frustrates passengers, and is leading to further decline consumer confidence as well as in air traffic demand. In Europe, the adoption of unilateral or uncoordinated measures is likely to lead to restrictions on free movement that are inconsistent and fragmented. In response to this situation, the European Commission made a proposal for a Council recommendation on a coordinated approach to travel restrictions following the principle of proportionality Following the rapid increase of COVID-19 cases in parts of England in December 2020, the recommendation on a coordinated approach to travel and transport measures was adopted [35]. In an early phase of the pandemic EUROCONTROL developed scenarios accounting for uncoordinated measures. The analysis implies that an uncoordinated approach will significantly impede the rate of a recovery [33]. Based on the experience in China it was assumed that intra-European traffic is returning first. However, the figures reported, e.g., for November 2020 by the German international airports show that air passenger volume is down by 89.6% for European flights, and by 91.8% for non-European flights, respectively. Furthermore, one should note that in 2019 about 18.6% of the air passenger volume was due to flights within Germany, 63.7% was due to flights within Europe, and 17.6% corresponded to non-European flights. This highlights that the decision-making process should be ensure coordination of the measures implemented by national and international authorities. Furthermore, overall national strategies for adjusting public health and social measures should be adequately considered. Any subsequent measure must be proportionate to public health risks [120]. With regard for the intra-European traffic, this is of particular

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importance. However, according to the experience of 2020 the lack coordination on international and European level can be expected to continue for the time being

Economic situation

The COVID-19 pandemic has a severe negative economic impact. The fear of a total collapse of advanced countries health system gave birth to what has been called the lockdown of major economies. However, mandatory closures do have a severe impact on the world economy and employment, and in particular the production of non-essential goods and services. The economic cost of the lockdown increases with duration of the lockdown situation [60, 124]. At some point, there will be irreversible economic consequences as the number of bankruptcies is reaching a critical mass. According to Sapir [100], various governments seem to underestimate the gravity and the complexity of the situation. They also continue to underestimate the extent of the COVID-19-induced recession. This is reflected in revisions of GDP growth forecasts [17].

As in the global financial crisis of 2008/2009, countries are affected differently. The currently available evidence indicates that countries depending more on tourism revenues show significantly greater negative growth revisions than countries where tourism plays a less pronounced role [43, 60, 68, 87]. If the pandemic requires prolonged and repeated lockdown or repeated partial closure of non-essential services, then the outcome for economic well-being in terms of consumption and production could be dramatic [76, 116]. It is to be expected that the tourism industry in particular will be more affected than other sectors [28, 85, 116]. In turn, this will have a considerable negative effect on the air transportation sector resulting in longer periods of recovery.

Estimates show that world recovery of passenger demand to pre-COVID-19 levels might take at least up to about 5 years (recovery in 2026). In addition, the currently available forecast results show large regional differences with Europe recovering later than North America and the Asia-Pacific region [34, 49, 57]. The air transportation sector is known as a driver of the economic and social development of a country [55, 105] and passenger activity has been shown to be a good indicator of economic growth [45]. Therefore, the end of mandatory lockdown measures and recovery from the current pandemic are not to simply jump-start the air transportation demand. Instead, some more disruptions and shocks, albeit of lesser extent, are to be expected over the next few years.

Results

This section presents the results of the prediction analysis aimed at providing practical estimates of the air traffic passengers and the financial performance of Frankfurt and Munich airport operators based on EBITDA. As explained in detail before, the development of indicative scenarios that are suitable for predicting the evolution of air passenger volumes is a difficult task under the current circumstances. The three scenarios considered here are explained below and shown in figure 8 for Frankfurt airport. Scenario 1 is based on the realistic air traffic scenario described by EUROCONTROL [34], where effective vaccines are widely available for travelers. This scenario assumes the end of the pandemic by summer 2022 with a return to 51% of 2019 air traffic volumes. Under this scenario, air traffic recovers to a level of 92% by 2024 with 2019 levels reached fully in 2026. In order to map the EUROCONTROL air traffic scenario onto a suitable air passenger scenario, here, it is assumed that the ratio of air traffic passenger volume to air traffic volume remains constant, i.e., the observation that this ratio varies during the course of the pandemic as shown in table 2 is neglected. Furthermore, as starting point for forecasting, the reported number air traffic passengers from December 2020 is taken. It should be noted that this scenario draws a rather optimistic picture, as is requires a steep Scenario 2 corresponds to a mean-reversion scenario where regression towards the expectation value at a given time is modelled by using a simple arithmetic Ornstein-Uhlenbeck process. This corresponds to a continuous time version of a first-order autoregressive process in discrete time (cf. [27], p. 76). Under this scenario, 2019 levels of air traffic passenger volume are reached fully in 2026. The speed of reversion is moderate and adjusted to that for the last phase (from 2023 onwards) of scenario 1.

Scenario 3 assumes that after initial production shortages vaccines are widely available. Vaccine is prioritized to adults over 60 years old in order to minimize mortality rather than to minimize cumulative incidence [18, 78]. Furthermore, novel mutations and regional outbreaks occur with high incidence rates which provokes uncoordinated non-pharmaceutical measures taken by governments such as partial lockdown, travel restrictions, mandatory quarantine, and chargeable PCR testing. The implemented government actions are assumed to adversely affect travel, economy, and consumer confidence. Under this scenario, the air traffic passenger volume is recovering slowly. For Germany, the rate of a recovery is lower than that for Europe and the rest of the world. Again, 2019 levels are reached fully in 2026. Overall, in all cases the stochastic air passenger model and the stochastic EBITDA functional are calibrated on the historical data of 2019 and 2020. For reference, projection calculations are carried out for the year 2019. The beginning of 2020 is chosen as starting point for the projection calculations up to 2026. For 2020, the monthly reported passenger data were used to calibrate the stochastic passenger model. At the beginning of 2021, the projection calculation branches into the different scenarios at 18.3% of the December 2019 level for Frankfurt airport. For Munich airport, the projection calculation branches into the different scenarios at 7.2% of the December 2019 level which is significantly less than the level for Frankfurt airport. The prediction accuracy has been set at 90% and 98% confidence

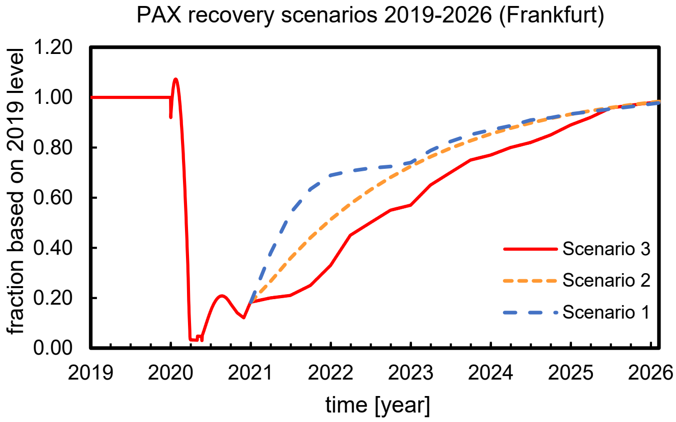

Figure 8: Scenarios with recovery in 2026: (1) vaccine available; (2) moderate mean reversion; (3) slow recovery due to regional outbreaks with high incidence rates and provoked government actions.

Frankfurt airport

	Scenario 1		Scenario 2		Scenario 3		Δ(0.90)		Δ(0.98)	
Year	PAX	EBITDA	PAX	EBITDA	PAX	EBITDA	PAX	EBITDA	PAX	EBITDA
2019	70.56	1180.3	70.56	1180.3	70.56	1180.3	±3.02	±70.4	±4.84	±112.8
2020	18.76	–26.8	18.76	–26.8	18.76	–26.8	±0.76	±17.7	±1.10	±25.6
2021	35.85	371.4	25.28	124.9	16.15	–87.7	±2.93	±68.2	±4.69	±109.3
2022	50.55	713.9	44.42	571.1	34.76	346.0	±3.79	±88.3	±6.07	±141.5
2023	57.84	883.8	56.12	843.7	49.15	681.3	±4.49	±104.6	±7.19	±167.6
2024	64.04	1028.3	63.39	1013.2	59.37	897.5	±5.10	±118.9	±8.18	±190.6
2025	67.32	1104.8	67.55	1110.1	68.09	1093.6	±5.63	±131.1	±9.02	±210.2
2026	69.99	1167.0	70.16	1170.9	71.47	1170.9	±6.17	±142.6	±9.80	±228.5

Munich airport

	Scenario 1		Scenario 2		Scenario 3		Δ(0.90)		Δ(0.98)	
Year	PAX	EBITDA	PAX	EBITDA	PAX	EBITDA	PAX	EBITDA	PAX	EBITDA
2019	47.96	554.3	47.96	554.3	47.96	554.3	±2.05	±42.3	±3.29	±67.7
2020	11.12	–205.3	11.12	–205.3	11.12	–205.3	±0.34	±6.9	±0.54	±11.0
2021	24.31	66.7	13.17	–163.0	6.33	–303.9	±1.74	±35.8	±2.78	±57.3
2022	34.36	273.9	27.89	140.5	20.15	–19.1	±2.25	±46.3	±3.60	±74.2
2023	39.32	376.2	36.87	325.7	31.10	206.6	±2.66	±54.8	±4.26	±87.8
2024	43.53	463.0	42.44	440.5	38.57	360.6	±3.02	±62.3	±4.85	±99.9
2025	45.76	509.0	45.65	506.6	45.24	498.2	±3.34	±68.7	±5.34	±110.2
2026	47.57	546.3	47.65	548.0	47.65	548.0	±3.63	±74.7	±5.81	±119.8

Table 3: Forecasting results for Frankfurt and Munich airports for the three scenarios considered. The calculations for 2019 and 2020 are based on reported passenger data. The COVID-19 projection starts at the beginning of 2020. The prediction accuracy for confidence intervals of 90% and 98% is also given. PAX values are given in million, and EBITDA values are given in million Euros.

interval. For Frankfurt airport, the noise term in equation (2) was arbitrarily set to 9670 for 2019 and to 5130 otherwise. For Munich airport, the noise term was set to 6570 for 2019 and to 3040 otherwise. For both airports, this corresponds to 5% and 10% of the average daily air passenger volumes for 2019 and 2020, respectively. These values should reflect the statistical spread reasonably well. The higher percentage for 2020 and beyond accounts for the higher unpredictability in air traffic during the pandemic. It should be noted that according to equation (2), by using fixed absolute values for the noise term absolute boundary values for a given confidence interval are obtained, i.e., the absolute spread at a given time point is independent of the scenario. This simplifies the calculations significantly but limits the forecasting capabilities for too large periods in time.

The forecast results for the three scenarios are summarized in table 3. The air passenger volume forecast for Frankfurt airport is plotted in figure 9 for scenario 3 together with a Monte Carlo sample path (blue line) and generated passenger data points (grey) at 2019 level with some outliers. The calculated 98% confidence interval is indicated by the dashed red lines. The corresponding monthly EBITDA forecast is shown in figure 10 for the period 2019-2024. For the period April to June 2020, the model calculates an EBITDA of –91.3 ± 10.1 Million Euros. In comparison, as reported in the FRAPORT interim report, the EBITDA for this period is –106.5 Million Euros (cf. [39]). These results show that the calibrated, simple passenger model in conjunction with the EBITDA model calculates the financial performance at the beginning of the pandemic reasonably well. It should be noted, however, that the model used here does not take into account, for instance, adjustments to personnel expenses or other measures to optimize EBITDA.

The results given in table 3 show that even for the rather optimistic EUROCONTROL scenario 1 the impact on the financial performance is severe, with a calculated decline in 2021 of about 68% for Frankfurt airport and 88% for Munich airport, respectively. Furthermore, the lower December level for Munich of 7.16% as compared to the level for Frankfurt airport of 18.26% implies that for this scenario the air traffic volume for Munich airport and, hence the air passenger volume, would have to recover at a rate approximately 3% faster than that for Frankfurt airport. Due to the strong correlation of the volume of monthly air passengers between Munich and Frankfurt airports under normal global economic conditions (see figure 2) and the strong dependency on the operation strategy of Lufthansa with Frankfurt as primary hub and Munich as secondary hub, this seems rather unlikely (cf. [83], p. 109). Furthermore, it should be noted that Lufthansa is the largest German airline which, when combined with its subsidiaries, is the second largest airline in Europe in terms of passengers carried. In conclusion, for Munich and especially for the other German airports, this scenario paints a too optimistic picture. For Munich airport, the forecast EBITDA for the three analyzed scenarios is shown in figure 11. A noticeable recovery starts around mid of 2023. The 2019 level is reached slowly by 2026.

A slow recovery in 2021 similarly to scenario 3 seems to be more in line with how the pandemic is evolving and the actions governments on national and international level are per default focusing on. The calculated results for this scenario suggest that a noticeable recovery will not occur until mid of 2022. It will then take at least another one to two years to compensate for the loss in revenue and the loss in consumer confidence.

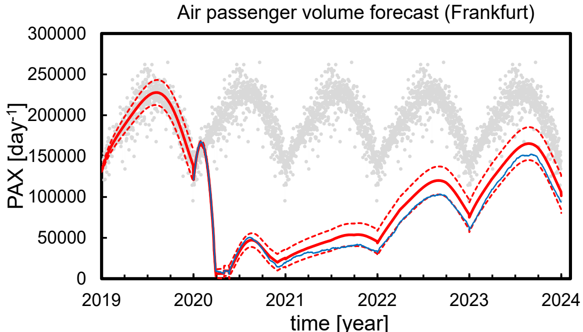

Figure 9: Air passenger volume forecast result for Frankfurt airport for scenario 3. For 2019 and 2020, the calculation is based on the reported data. A stochastic sample path is plotted in blue. The grey points represent generated passenger data with some outliers. The dashed red lines indicate the 98% confidence interval.

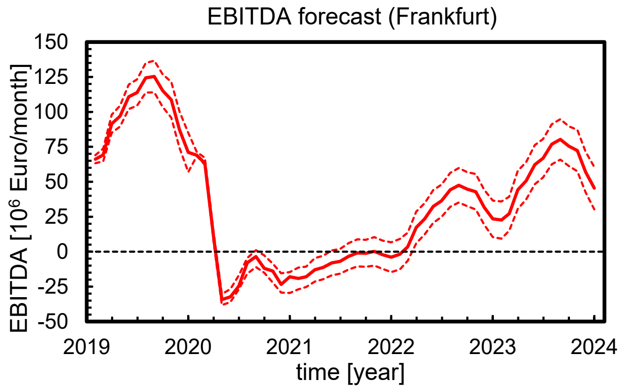

Figure 10: EBITDA 2019-2024 forecast for Frankfurt airport based on the stochastic passenger model. The dashed red lines indicate the 98% confidence interval. For 2019, a separate calculation has been carried out. Based on reported passenger data, the forecast starts at the beginning of 2020 and branches into scenario 3 from 2021.

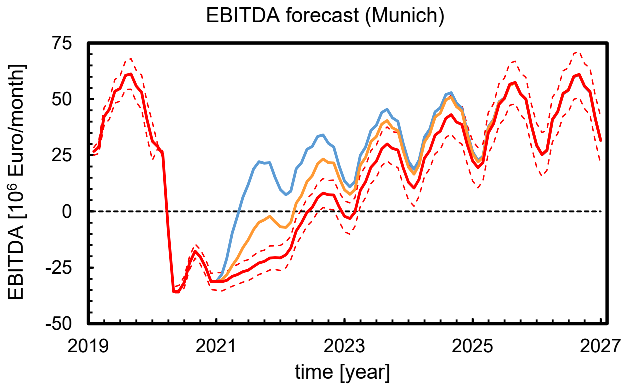

Figure 11: EBITDA 2019-2026 forecast for Munich airport based on the stochastic passenger model. Based on reported passenger data, the forecast starts at the beginning of 2020 and branches into the three scenarios considered here. The blue line is the forecast based on the EUROCONTROL scenario 1, the orange line corresponds to the mean reversion scenario 2, and the red line corresponds to scenario 3. The dashed red lines indicate the 98% confidence interval of scenario 3.

Conclusions

In this work, stochastic equations with Gaussian white noise have been used to model the air passenger volume in a given time frame. Based upon the stochastic passenger model, three COVID-19 recovery scenarios were simulated that range from a rather optimistic course of recovery to a more pessimistic one that seems more realistic about government actions likely to be taken on national and international levels. The major factor behind a slow recovery in air travel appears to be the combination of travel restrictions and a lack of international cooperation, leading to a fragmented market situation in Europe and affecting consumer confidence. A correlation analysis shows that the EBITDA can be written as a functional of the stochastic air passenger volume. Projections of the EBITDA carried out for the two largest

German airports suggest that the impact on the financial performance is severe. A noticeable recovery is unlikely to occur until mid of 2022. The analysis presented here is subject to a number of limitations. The available data did not allow a reliable derivation of the statistical spread for use in the noise term. In addition, adjustments to personnel expenses or other measures to optimize EBITDA were not taken into account. Passenger-independent contributions to the EBITDA were neglected. However, it could be demonstrated that the method described here is suited for projection calculations.

Compliance with Ethical Standards

The author declares no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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