Managing Common and Catastrophic Risks in the Airline Industry

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Abstract This chapter discusses risk management with a focus on the airline industry. The world has become acutely aware of major supply chain disruptions due to the COVID pandemic. Consumers, airline passengers, and companies are scrambling to understand and respond to these events. In that light, we begin the chapter with a brief overview of risk management, highlighting both common and catastrophic risks faced by companies and their supply chains. We then discuss approaches that companies employ to mitigate them. Our primary goal is to explore the risks that airlines face and the approaches they take to manage them, including fuel hedging, capacity management, and ticket pricing. Based on company interviews and our firsthand experience, we note that the airlines typically make these decisions in silos. Therefore, we introduce an analytical model that explicitly integrates them. We derive analytical results and propose directions for future research. We conclude with summary comments about managing risks once the world moves past COVID.

Keywords Supply chain risk management · Airline risk management · Fuel cost · Hedging · Airline pricing · Airline capacity management

1 Introduction

Dr. Morris Cohen has studied risk management in a variety of contexts over many years. From his extensive research on inventory management, and in particular, service parts inventory (Cohen et al. 1986, 1999; Deshpande et al. 2003; Guajardo

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H. Lee et al. (eds.), *Creating Values with Operations and Analytics*, Springer Series in Supply Chain Management 19, https://doi.org/10.1007/978-3-031-08871-1_13

and Cohen 2018, to cite just a few), to work on operational flexibility and exchange rate risk with Arnd Huchzermeier (Huchzermeier and Cohen 1996), to recent strategic perspectives on disruptive shocks (Cohen and Kouvelis 2021), Dr. Cohen has inspired many students, colleagues, and researchers worldwide to advance this critical area. This chapter builds on Dr. Cohen's research as we examine risk management with a focus on the airline industry. In Sect. 2, we provide a brief overview of risk management, highlighting approaches to managing high probability common risks and low-probability catastrophic risks. Section 3 discusses risks and risk management in the airline industry. In Sect. 4, we introduce an analytical model for coordinated risk management for an airline, and in Sect. 5, we provide summary comments and thoughts about managing risks once the world moves past COVID.

2 Defining and Managing Risk

Risk is often defined as the probability of an event (typically negative) and its impact. Risk management is a process designed to identify potential events that may affect a company or other entity and to manage the risks to be within its risk appetite. Thus, risk management entails event identification, assessing the likelihood and impact of these events, and responding to them. Risk responses may be taken in advance of an event by, for instance, avoiding, reducing, or sharing the risk or by reacting and recovering should adverse events occur.

Figure 1 illustrates risk likelihood and impact and has provided a useful way for companies to categorize the severity of potential adverse events. Abstracting from Fig. 1, one can think of two primary categories of risk—high-probability common risks and low-probability catastrophic risks.

Impact

Likelihood

	Negligible	Low	Moderate	Very High	Extreme
Almost certain	Moderate	Major	High	Serve	Severe
Likely	Moderate	Significant	Major	High	Severe
Moderate	Low	Moderate	Significant	Major	High
Unlikely	Very low	Low	Moderate	Significant	Major
Rare	Very low	Very low	Low	Moderate	Significant

Fig. 1 Risk likelihood and impact

Common risks include, for instance, normal fluctuations in currency exchange rates. In the supply chain context, they include moderate delays in shipments and fluctuations in demand. Shipment delays can be due to weather events, such as snowstorms, delays at customs, queues at ports, and so on. Fluctuations in demand can be the result of competitor pricing, promotions, weather, and other underlying randomness in consumer behavior.

There has been extensive research, as well as developments in software and business processes, on managing common supply chain risks. For example, setting inventory levels optimally can both improve service and reduce costs. Dr. Cohen's research has been highly influential in this area. The use of time buffers can help mitigate the impact of shipping delays. These tools can reduce the impact of the relevant risks without changing their likelihood. A potentially more powerful approach is to reduce the variability of demand or lead time by employing advances in supply chain coordination. Sales and Operations Planning (S&OP), for instance, aims to provide the operations and supply chain functions with advanced notice of, say, sales promotions or new major contracts. It also can provide the Sales team with awareness of capacity constraints or inventory shortages. S&OP is a process that is often internal to the firm. Coordination with supply chain partners expands the communication to upstream and downstream companies. Coordinated Planning, Forecasting and Replenishment (CPFR) and Vendor Managed Inventory (VMI) allow firms to plan in advance for promotions, capacity constraints, inventory challenges, and other disruptions. These tools can decrease the likelihood of adverse events by providing early notification.

Low-probability, highly disruptive events are represented toward the right lower corner of Fig. 1. These include extreme weather or geologic events, such as the tsunami that inundated Fukushima, Japan in March of 2011 or the Eyjafjallajökull, Iceland volcano eruption in April of 2010. In both cases, important supply chain participants were affected. It was no surprise that suppliers in the Fukushima area shut down for an extended time. The Eyjafjallajökull eruption, on the other hand, created unanticipated effects. It released huge amounts of ash which soon disrupted 29% of global air traffic. Within days, factories as far away as Cleveland shut down for lack of components. Other catastrophic events in recent memory include the Great Recession of the late 2000s, the Asian financial crisis of the late 1990s, and of course the COVID-19 pandemic.

Perhaps one positive outcome from the COVID pandemic is the increasing awareness among journalists and the broader public about supply chains. Early reporting was frustratingly inaccurate and had glaring gaps. For example, CNN reported on April 29, 2020 that "public, private health labs may *never* be able to meet demand for coronavirus testing over supply chain shortages," (emphasis added) even though no one could figure out the reason for the shortages. One cause was eventually identified as nasal swabs, for which there were only two CDC-approved manufacturers in the world. As it happens, both companies were located in regions severely impacted by COVID, and neither was (not surprisingly) prepared for the dramatic surge in demand. A famous quote is certainly fitting: "*For want of a nail, the shoe was lost. For want of a shoe, the horse was lost. For want of a horse,* *the rider was lost. For want of a rider, the battle was lost*." Of course, testing requires many more components than swabs, suggesting numerous potential points of failure for the supply chain. See the Sidebar: components of the Molecular Testing Process for a, perhaps not exhaustive, list of components required.

Sidebar: Components of Molecular Testing Process

Lab Personnel to Prepare Kits
Lab coat
Gloves
Mask

Kit
Box
Foam
Tubes
Swabs

Transport Medium
Hanks Balanced Salt Solution (HBSS) 1X with calcium and magnesium ions
Heat-inactivated fetal bovine serum
Gentamicin sulfate
Amphotericin B

Tester
Sanitizer
Gloves
Gown
Mask
Face shield/protective eyewear

Patient
Sanitizer
Face mask

Lab Tech Taking Sample
Lab coat
Gloves
Mask

Test Prep
Primer/probe mixes
Positive control
Human specimen control
Enzyme master mix
RNA extraction kit

Running the Test
Vortex mixer
Microcentrifuge
Micropipettes
Multichannel micropipettes
Racks for microcentrifuge tubes
Cold blocks
PCR system and software
Extraction system instruments
Molecular grade water
Bleach
DNAZap
RNAse Away
Aerosol barrier pipette tips
Microcentrifuge tubes
PCR reaction plates

Storage
Box
Foam
Cold block
Ice pack
Dry ice if needed for shipping

Reducing the likelihood of these catastrophic events may be impossible. However, it may be feasible to reduce their impact, even though costs may increase in the process. Many companies have developed explicit backup plans that they can deploy if an adverse event occurs. Some firms retain multiple suppliers in different regions, being careful to account for political stability, currency exchange rates, lead times, and shipping lanes. Others maintain excess capacity or inventory. Tesla employs in-house software engineering expertise and uses chips that can perform multiple functions, which has enabled the company to remain somewhat immune from the global shortage of semiconductors during the pandemic. Having visibility to extended layers of the supply chain is valuable as well. Recently, some supply chains have implemented blockchain solutions to enhance visibility and transparency. Finally, it may be possible to buy insurance or to share risk in other ways with supply chain partners. Because the literature on risk management is enormous, we point the reader to one excellent overview, Kouvelis et al. (2012), and the references therein.

3 Risk Management for the Airlines

Airlines face enormous risks that range across both the common and catastrophic categories, some of which mirror those mentioned in the previous section. Their common risks include fluctuations in fuel prices, variations in passenger demand, weather delays, and variable currency exchange rates. A major operational goal of the airlines in managing these risks is achieving and maintaining high load factors. The load factor is the ratio of passenger miles traveled to available seat miles (ASMs), and as such is a measure of capacity utilization. ASM is a measure that counts the total available seats in one mile of flight operation. Because the cost of an additional passenger is very small relative to the incremental revenue, high load factors are critical to airline profitability. In the early 2000s, average load factors for U.S. airlines in the domestic market hovered around 65% to 75%. In the few years before COVID, load factors had increased to around 85%, significantly improving profitability. To achieve these load factors, airlines carefully manage capacity and pricing. Capacity (or ASM) can be managed by adjusting both flight frequency on given routes and aircraft size. Travelers will notice variations in the number of flights per day on a given route, depending on the season, the state of the economy, and other factors. Aircraft size, for this purpose, is defined as the number of seats on the plane. Typically, aircraft manufacturers introduce a base model or platform that can be extended to several new versions. These extensions thus can increase the number of seats without major adjustments to staff training. The Boeing 737-700, for instance, has 137 seats, while the 737-800 has 175, and the 737 Max has 200. Minor adjustments can be made within each model by “upgauging” or adding seats to existing aircraft. Airlines can increase the number of seats on the 737-700 to 143 by installing new seats or decreasing legroom. Major changes to ASM and flight frequency can take months, and of course purchasing new aircraft involves very long lead times. Over the past 18 years, flight frequency for domestic airlines has generally decreased, while aircraft size has trended higher, although with significant short-term variability. Average ASM for these airlines fluctuates but clearly tracks the state of the U.S. economy. (See Pyke and Sibdari 2019.)

Fuel is either the highest or the second highest component of airlines’ operational costs, depending on fuel cost fluctuations. Not surprisingly, the average cost per gallon of jet fuel very closely tracks the price of crude oil. In the past two decades, crude oil has increased from $20 per barrel to nearly $140, just prior to the Great

Recession. Oil plummeted in 2008 to around $40 per barrel, before increasing to over $100 as the economy recovered. At this writing, a barrel of West Texas Intermediate is around $77. One approach the airlines have used, with mixed success, in response to these severe fluctuations is hedging fuel costs. Southwest famously hedged around 70% of their fuel consumption prior to 2008, when the spot price was about $100. The financial results were extremely positive, which led other airlines to aggressively hedge fuel costs. Unfortunately, when prices collapsed in 2008, some airlines amassed huge losses because of poor hedging bets. Some airlines abandoned hedging altogether, while others continued, with perhaps more sophistication. The pandemic again dealt a blow to hedging policies, as capacity and oil prices declined sharply. Airlines that locked in a quantity of fuel to purchase at a specified price were faced with the obligation to buy fuel that they did not need. In its 2020 Annual Report, Lufthansa reported that the significant drop in capacity and oil prices due to the pandemic meant that it was over-hedged, and its hedging losses could not be recouped by lower fuel expenses.

Airlines can use a variety of hedging strategies, including futures contracts, call and put options, and swaps. They may also employ a complicated mix of these and other strategies. Each strategy has advantages and disadvantages, depending on the level of risk the airline wishes to accept, the premium built into certain strategies, and the actual market outcome. Some strategies limit the airlines' exposure to higher prices but do not provide benefit should prices decrease. Other strategies allow airlines to have the best of both situations, i.e., paying the market price when prices decrease, and hedging when prices increase, but these strategies come with an upfront premium expense.

For airlines that operate or purchase items globally, currency exchange rate fluctuations can impact profitability. As a result, many hedge relevant currencies. At one global airline, subsidiaries report exposure to 65 foreign currencies. Some of these are hedged using financial instruments, while some are aggregated to create natural hedges. A natural hedge occurs when cash inflows and outflows in different currencies net out and thus reduce exposure. Firms can also manage natural hedges by collecting revenues in the currency they use to pay costs. Residual risk is then managed by using financial hedges.

A powerful tool airlines use to manage load factors and profitability is pricing and revenue management. Revenue management employs sophisticated mathematical algorithms based on the time remaining until a flight's departure date, the open seats on the flight, and the forecast of demand. These algorithms maximize expected revenue, while accounting for possible overbooking and any associated financial penalties and loss of customer goodwill. Prices can change daily and even hourly in some cases.

Before we introduce a model that analyzes three approaches to managing common risks (fuel hedging, capacity management, and pricing), we first briefly discuss low-probability, highly disruptive risks in the airline context. At this writing, the world is entering year 3 of the COVID pandemic, and many people are keenly aware of the catastrophic risks faced by the airlines. While the Fukushima tsunami had a long-term impact on many companies and supply chains, the effect on global airlines was limited. Macroeconomic swings, on the other hand, can profoundly influence airline profitability. The Asian financial crisis, the recession after 9/11 and the tech crash of the early 2000s, and the Great Recession, all led to significant distress for the airlines. In addition, competition on given routes from low-cost airlines can fundamentally alter an airline's profitability. As we have observed recently with COVID, airlines respond to such events by decreasing capacity, canceling aircraft orders, and selectively furloughing or laying off pilots and staff. Furthermore, the industry has experienced many bankruptcies, mergers, and restructurings over the past few decades. Airlines are intentional about outsourcing certain routes to subsidiaries or independent regional airlines. As well, the industry has relied on government bailouts when available. Over the first two years of the pandemic, the U.S. Congress passed several airline relief programs that awarded $54 billion in grants to U.S. airlines, with the condition that they would limit dividends, layoffs, pay increases for senior executives, and stock buybacks. In April of 2020, the government also awarded $10 billion to airports as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act. The FAA adjusted training requirements, air traffic control tower hours, and requirements for temporary parking for aircraft. Even with these measures, flights may be canceled at an alarming rate. At this writing during the holiday season of 2021, thousands of flights are being canceled because of COVID-related staff shortages (as well as severe winter weather).

As noted above, these actions may limit the impact of catastrophic events, but they cannot change their likelihood. On the other hand, it may be possible for airlines to influence both the likelihood and impact of common risks by employing hedging, capacity management, and revenue management tools. From our experience with airlines and discussions with airline executives, however, it is evident that these three decisions are handled in different departments, with limited communication among them. We are interested in examining the potential improvement in profitability if the airlines made these decisions in an integrated way. We begin to address this issue by introducing an analytical model in the next section.

4 Model for Integrated Risk Management: Maximization of Expected Profit

In this section, we present a stylized model of an airline's decisions on fuel hedging, capacity, and pricing, and we propose an integrated approach that explicitly links the decisions. The airlines make these decisions at different times with respect to a given flight. Hedging decisions are generally made infrequently and are established well in advance of a given flight. Capacity adjustments can be made several months before a flight, but once the flight is posted for passenger booking, airlines are reluctant to change the number of seats. Indeed, they may pay a penalty if a change results in passengers being bumped. Pricing decisions, on the other hand, can be made very frequently and very close the actual flight. Therefore, we consider the three decisions in sequence: percent of fuel to be hedged (h), followed by capacity (k), and finally average price (p), with the objective of maximizing expected profit.

Passenger demand is a function of price, with a random shock to account for underlying demand variability. To facilitate the analysis, we define average price in terms of \$/seat-mile. Capacity is measured by ASM, or the total number of seat miles flown, and the profit function includes a term for the product of capacity, k, and actual fuel cost per seat-mile (CPS). We define the hedging decision, h, as the percentage of total fuel consumption to be hedged. Fuel cost (c) is variable and is measured in \$/seat-mile. As noted above, airlines may use a mix of hedging strategies, some of which build in a premium that accounts for the risk to the other party in the contract. Our stylized model does not attempt to capture the complexity of the possible hedging strategies. Rather, we assume that hedging removes fuel cost uncertainty for the portion of fuel consumption that is hedged, but this requires a premium. We define this premium as a factor, m, and assume that it increases with the standard deviation of c.

Clearly, reality is much more complex than our stylized model, but our ultimate intent is to gain insights that are valuable to airline management and that can lead to a more comprehensive analysis. We first introduce relevant notation, summarized in Table 1, and the objective function. For this model, the objective function maximizes expected profit in a non-competitive context. Later research will address the maximization of a mean–variance formulation, which accounts for risk aversion, as well as a set of numerical results based on representative airline data. To facilitate the current analysis, we rewrite the airline's capacity in terms of a "stocking factor." Finally, we solve the model sequentially by assuming a fixed capacity and hedging percentage and solving for the optimal average price. Given the optimal price, we then solve for the optimal capacity and finally the optimal hedging percentage.

Table 1 Summary of notations

Symbol	Definition
p	Average airfare (decision variable), $\$/seat\ mile$
k	Airline's capacity (decision variable), available seat-miles (ASMs) $ASM = total\ number\ of\ seats * miles\ of\ flight$
h	Percentage of hedging (decision variable)
$D(p) = a - bp + \varepsilon$	Demand, which depends on the airfare and is random
ε	Demand shock that is airfare independent. Let $F(x)$ and $f(x)$ be the distribution and density function of ε, respectively. In addition, let $\bar{F}(x) = 1 - F(x)$. Without loss of generality, we assume that $E(\varepsilon) = 0$. $STD(\varepsilon) = \sigma_d$. The lower and upper limits of the domain for ε are l_d and u_d, respectively
c	Fuel cost ($\$/seat\ mile$). Let $G(x)$ and $g(x)$ be the distribution and density function of c, respectively. $E(c) = \mu_c$ and $STD(c) = \sigma_c$
m	Premium for hedging which increases with σ_c

4.1 Objective Function and Sequence of Events

For a given airfare p, capacity k, percentage of hedging h, realization of ε, and the airline's actual fuel cost per seat-mile (hereafter, CPS for short), the airline's profit is $p \min[a - bp + \varepsilon, k] - kCPS$. Taking the expectation with respect to ε and CPS, we obtain the expected profit of the airline

$$\pi(h, k, p) = pE\, min[a - bp + \varepsilon, k] - k[hm\mu_c + (1 - h)\mu_c]. \tag{1}$$

Note that if $\sigma_c = 0$, then $m = 1$; i.e., if there is no variability, the airline would have no incentive to hedge, and its expected fuel cost would be μ_c. On the other hand, if $\sigma_c > 0$ and a firm offers the airline a no-premium contract (i.e., $m = 1$), the airline could eliminate variability at no cost and therefore would have an incentive to hedge all of its fuel purchases. If $m < 1$, the airlines would have an arbitrage opportunity that does not exist in such contracts. Therefore, in our model, we restrict m to be greater than 1.

The sequence of events is given as follows. First, the airline determines the percentage of hedging, h, to maximize its expected profit. Second, the capacity decision, k, is determined by the airline. And lastly, the airline decides on the price (i.e., airfare) to charge to the consumers. We solve the problem backward (see the analysis below) by first solving for the airfare p, and then the capacity k, and lastly the hedging percentage h.

4.2 Analysis

We present the analysis of solving the game in this subsection. First, we show how the price (i.e., average airfare) is determined.

To facilitate the analysis, we write the airline's capacity k in terms of the airfare p and a *stocking factor* z; specifically, $k = a - bp + z$. The airline's expected profit in Eq. (1) can be written as

$$\begin{aligned}
\pi(h, k, p) &= pE\, min[a - bp + \varepsilon, a - bp + z] - (a - bp + z)[hm\mu_c + (1 - h)\mu_c] \\
&= p(a - bp) + pE \min(\varepsilon, z) - (a - bp + z)[hm\mu_c + (1 - h)\mu_c] \\
&= p(a - bp) + p\left[\int_{l_d}^{z} xf(x)dx + \int_{z}^{u_d} zf(x)dx\right] \\
&\quad -(a - bp + z)[hm\mu_c + (1 - h)\mu_c].
\end{aligned}$$

Let $L(z) = \int_{l_d}^{z} xf(x)dx + \int_{z}^{u_d} zf(x)dx$. The airline's expected profit is

$$\pi(h,k,p) = p(a-bp) + pL(z) - (a-bp+z)[hm\mu_c + (1-h)\mu_c].$$

Using the first-order condition, we can obtain the optimal value of p, which is

$$p = \frac{a + b[hm\mu_c + (1-h)\mu_c] + L(z)}{2b}.$$

After obtaining the price p, we are ready to solve for the stocking factor k. Recall that $k = a - bp + z$. To get the optimal k, we need to obtain the optimal z value. Since $p = \frac{a+b[hm\mu_c+(1-h)\mu_c]+L(z)}{2b}$, $p'(z) = L'(z)/2b$. We also know that $L'(z) = \bar{F}(z)$.

Recall that the airline's expected profit is

$$\pi(h,k,p) = p(a-bp) + pL(z) - (a-bp+z)[hm\mu_c + (1-h)\mu_c].$$

Taking first-order derivative with respect to z, we have

$$\frac{d\pi}{dz} = \{a + b[hm\mu_c + (1-h)\mu_c] + L(z)\}\,\frac{\bar{F}(z)}{2b} - [hm\mu_c + (1-h)\mu_c].$$

Using the first-order condition, the optimal value of z satisfies

$$\{a + b[hm\mu_c + (1-h)\mu_c] + L(z)\}\,\bar{F}(z) - 2b[hm\mu_c + (1-h)\mu_c] = 0. \quad (2)$$

Last, the optimal hedging percentage h can be solved. From Eq. (2), we have

$$hm\mu_c + (1-h)\mu_c = \frac{[a + L(z)]\bar{F}(z)}{b[1+F(z)]}. \quad (3)$$

$$p = \frac{a + L(z)}{b[1+F(z)]}. \quad (4)$$

Using the airline's expected profit of

$$\pi(h,k,p) = p(a-bp) + pL(z) - (a-bp+z)[hm\mu_c + (1-h)\mu_c],$$

we plug (3) and (4) into (2), to get the airline's expected profit in terms of the stocking factor z as follows:

$$\pi(z) = \frac{a + L(z)}{b[1+F(z)]}\,\frac{aF(z) - L(z)}{1+F(z)} + \frac{a + L(z)}{b[1+F(z)]}L(z)$$
$$- \left[\frac{aF(z) - L(z)}{1+F(z)} + z\right]\frac{[a + L(z)]\bar{F}(z)}{b[1+F(z)]}.$$

Using the first-order condition, we obtain the optimal z value that satisfies

$$[aF(z) - L(z)]\,[a + L(z)][1 + F(z)]f(z) + zf(z)[a + L(z)][1 + F(z)]^2$$
$$+ \left\{[aF(z) + L(z)]\bar{F}(z) - [1 + F(z)]z\bar{F}(z)\right\}\left\{\bar{F}(z)[1 + F(z)] - [a + L(z)]f(z)\right\} = 0.$$

The following two lemmas characterize the airline's optimal airfare, optimal capacity, and percentage of hedging.

Lemma 1 *(i) The optimal airfare is* $p = \frac{a+L(z)}{b[a+F(z)]}$. *(ii) The airline's optimal capacity is* $k = \frac{aF(z)-L(z)}{1+F(z)} + z$. *(iii) The optimal airfare and airline's capacity are independent of the fuel cost and are solely determined by passenger demand.*

Lemma 2 *(i) The optimal percentage of hedging is* $h = \frac{p\bar{F}(z)-\mu_c}{(m-1)\mu_c}$.

It is a feature of the expected profit formulation that the optimal airfare and capacity are independent of fuel cost. Of course, the optimal percentage of hedging is dependent on fuel cost and the hedging premium. The optimal capacity is a function of passenger demand and the stocking factor, which is analogous to safety stock in an inventory system. However, none of the optimal values include σ_c. As noted above, future research will extend this formulation to account for risk aversion using a mean–variance formulation that, in addition to expected profit, incorporates a negative term with a risk aversion parameter and the variance of profit. Preliminary analytical results suggest that the optimal price, capacity, and hedging percentages each are complex functions of the other two decision variables, as well as the uncertainty in both passenger demand and fuel cost. We anticipate generating insights from the analytical results, in addition to those garnered from numerical results based on representative airline data. The goal is to yield insights into the potential for profit gain from integrating the three decisions, rather than making them in a decentralized way.

5 Summary

Regardless of the overall state of the industry as we emerge from the pandemic, the airlines will continue to face uncertainties in fuel cost and passenger demand. They will manage these mid- and short-term risks by selectively hedging, carefully managing capacity, and dynamically setting prices. We submit that their current decentralized approach to these decisions may be leaving profit on the table and that they will be well served to pursue a more integrated decision process. Enhancing communication and coordination among disparate groups can be extremely challenging. Many companies, for example, struggled to develop effective Sales and Operations Planning (S&OP) processes because of the differing objectives, and longstanding distrust, between sales and operations personnel. Nevertheless, with senior and functional area leadership, S&OP has become a valuable planning tool in numerous companies across a variety of industries. Our goal with this stream of airline research is to identify the potential profit gains from integrating these three key decisions. Such insights could spur senior leaders to undertake and support the hard work of creating effective processes and tools for joint optimization. In order to be convincing to industry leaders, however, it is important that data analyzed in the research be representative. In that light, we note the Bureau of Transportation Statistics, a source of free, massive and valuable databases that is aiding this research.

We close with some comments about leadership in the face of catastrophic risks, both for the airlines and for the broader business and public spheres. As the world recovers from COVID-19, the airlines may face a new normal. The disruption to the industry during the pandemic was unprecedented. By September 2020, passenger demand had declined by up to 75%, and by the end of 2020, it was down by 50%. Industry analysts and insiders suggested that it could take three to five years for the industry to return to normal operations (Calhoun 2020), while some say that it will never return. Whatever the outcome, in responding to this massive disruption, airlines surely will continue to use all the tools at their disposal. Some will not survive, and others will return but with more limited operations. No doubt some will thrive if worldwide demand rebounds, but it will take strong leadership, creativity, and vision to be in that group.

In the broader scope of global supply chains, the massive disruptions due to the pandemic have spurred firms to make some fundamental strategic and tactical shifts. Many have moved manufacturing or suppliers from China to Vietnam, Thailand, India, or other offshore locations. A number of firms have developed domestic or regional suppliers, resulting in reduced lead times but increased costs. The passion for lean supply chains has eased, and firms are more willing to hold additional inventory to buffer for long and uncertain lead times. They are looking carefully at their plans for risk mitigation and recovery, and they are seeking new ways to improve supply chain visibility. In the public sphere, governments are mandating stockpiles of personal protective equipment, ventilators, and other medical supplies. These actions seem wise and are certainly widely supported. Nevertheless, we are wary about the long-term commitment to these policies. Business and government leaders, due to incentives from the financial markets and voters, tend to have a decidedly short-term focus. Will they revert to a myopic focus on cost reduction at the expense of risk reduction? A brief episode from California may be instructive.

Shortly after Hurricane Katrina devastated New Orleans in 2005, then-governor Schwarzenegger announced that the state would invest more than $200 million "in a powerful set of medical weapons to deploy in the case of large-scale emergencies and natural disasters such as earthquakes, fires and pandemics." An impressive initiative followed with the acquisition of three 200-bed mobile hospitals that could be deployed within 72 h on 18-wheelers. These were fully insulated, HVAC-equipped, semi-permanent tents, each containing an emergency room, an intensive care unit, X-ray equipment, an operating room, and surgical wards. They were equipped with ventilators, a full complement of medications, and sleeping quarters for staff. In addition, the state stockpiled medicines and medical gear, including

50 million N95 respirators, 2,400 portable ventilators, and kits to set up 21,000 additional patient beds wherever they were needed. Just a few years later, in 2011, then-governor Jerry Brown came into office facing a $26-billion budget deficit. Among the ensuing cutbacks, the state eliminated the funds to store and maintain the stockpile of supplies and the mobile hospitals. As it happens, the hospitals were never used. Although much of the medical equipment was given to local hospitals and health agencies, the state did not provide any funding to maintain them. Respirators were allowed to expire without being replaced, and the supply of usable N95 respirators decreased to 21 million by the time COVID-19 arrived. The cost to maintain these programs was less than $5.8 million per year, on an annual state budget of about $129 billion. (See Williams et al. 2020.)

Will leaders, both business and government, take a long-term perspective that broadens their goals from a narrow focus on cost reduction? Will they be able to convince shareholders and voters that this perspective is worth the cost? We sincerely hope that our collective memory keeps alive the lessons from the pandemic.

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