Effects of Large-Scale Violent Events on the Demand for International Scheduled Air Traffic

Economists for Peace and Security for the Arsenault Family Foundation*
23 December 2011 [Final Report]

Abstract: The terror attack of 11 September 2001 ("9/11") on the United States put the threat of deadly violence from large-scale violent events very much in the public eye. The attack carried economic effects, not so much in terms of its direct as in its indirect costs. This suggests that the general level of real or perceived (in)security might have a long-term effects on corporate and industry performance, rather than simply having short-time shock effects that wear off over time.

It is widely thought that one of the affected industries of 9/11 was the global airline industry through the effect of the attack on global air traffic demand for international, scheduled flights. Using data from the International Civil Aviation Organization on various indicators of airline performance and variables derived from the Global Terrorism Database, this Report considers whether this was indeed the case. The main method of study applied is panel data analysis, focusing both on the whole available sample of 443 airlines and on a panel of the 20 largest airline companies. Exploratory case study analysis of a small selection of individual airlines is also undertaken.

We find that when one takes account of potential confounding factors such as the general state of the economy, global air traffic was not greatly affected by the general level of terrorist attacks worldwide, and that it takes a truly exceptional event such as 9/11 to find a measurable impact on air traffic. Even then, the measured effect for the industry as a whole is small in magnitude. The reason for this finding appears to be that the demand for international scheduled air flights is rather heterogeneous across airlines. Aggregating across the whole of the global industry is not in all instances warranted. The industry perhaps overstates the impact of particular large-scale violent events. While specific airlines suffer from specific adverse events, global air traffic demand for the industry as a whole appears fairly resilient to violent shocks.

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1. Introduction

1.1 First impressions

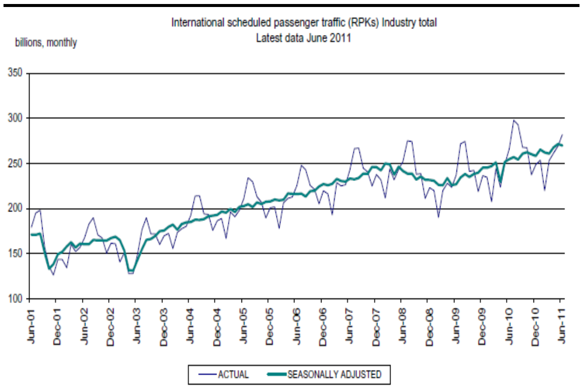

Figure 1: Revenue passenger kilometers (RPK) for international scheduled passenger traffic, June 2001 to June 2011, industry total.
Source: IATA (2011). See http://www.iata.org/whatwedo/economics/Pages/traffic_analysis.aspx [accessed 10 September 2011].

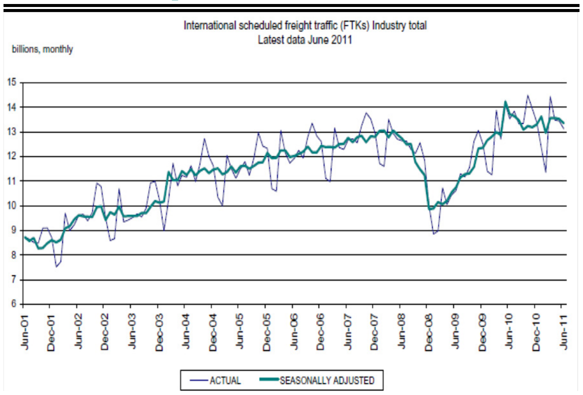

Figure 2: Freight tonne kilometers (FTF)
Source: See Figure 1.

On its website, the International Air Transport Association (IATA), a business group, publishes summary data on airline traffic and other variables. Figure 1 is taken from IATA. In it, the bold-type, smooth line reflects seasonally adjusted data for international scheduled passenger traffic and shows sharp declines in revenue-passenger kilometers flown (RPK) in the second half of 2001 as well as in the first half of 2003. At first sight, this could reflect, respectively, the 11 September 2001 (“9/11”) terror event and the combat phase of the Iraq war, which lasted from 20 March to 1 May 2003. The latter event, however, was completely overlaid by a pandemic threat caused by the appearance in Asia and consequent rapid global spread of Severe Acute Respiratory Syndrome (SARS), lasting from November 2002 through July 2003, so that the apparent drop in RPKs flown might be due to either, or both, events.

Freight traffic also appears to have been affected, although not in the same degree (Figure 2). In both cases, it is possible that the visually apparent effects on the airline industry perhaps do not stem so much from violence (terror and war) as from pandemics, financial crises, or natural catastrophes such as volcanic eruptions, earthquakes, or hurricanes. The possible effects of the world financial crisis of 2008/9, for example, would seem clearly visible—and far more severe and long-lasting—in both figures.

Nonetheless, in the months after 9/11, the global airline industry, i.e., IATA, lamented the billions of dollars of losses on account of the event (due both to higher cost and to lower revenue). Air traffic demand appeared to drop sharply, beyond what might be explained by seasonality alone. While airline companies were struggling financially before the attack, it seems that their prospects worsened significantly following it (Ito and Lee, 2005a; 2005b), and a bevy of major airlines declared bankruptcy, e.g., Sabena in 2001 and Air Canada in 2003.

The pattern in Figure 1 also holds—albeit in different degree and with different emphases—in regional sub-samples for airline traffic in Africa, Asia/Pacific, Europe, Latin America, the Middle East, and North America. As regards international scheduled freight traffic, however, except for North America, only the world financial crisis of 2008/9 appears to have affected continental-sized regional airline markets.

1.1 Brief review of extant papers

For obvious reasons, the news industry has paid much attention to the purported effects of the 9/11 atrocity, together with general analyses of the impact of terrorist incidents. In contrast, surprisingly little solid empirical work is present in the practitioner (trade and consulting) and academic literatures. A recent example from the consulting arena is offered by the OAG Aviation (2011) consultancy's *World Crisis Analysis Whitepaper* which purports to present an analysis of the effects of security and other events on the global airline industry, for instance of the Icelandic volcanic eruptions in 2010 on European air travel, but is in fact striking in its superficiality and lack of empirical sophistication.[1]

Within the academic literature, Ito and Lee (2005a; 2005b) measure the effect of the impact of 9/11 on domestic U.S. airline demand and international airline demand, respectively. In both cases, they use aggregate data obtained from the U.S. Air Transport Association, the Association of European Airlines, and government organizations such as those in Canada and Australia.[2] Using revenue-passenger kilometers (RPKs)—except for Australia, where the authors use the number of passengers flown—they find a statistically significant adverse impact of 9/11 on air traffic demand but argue that this effect was quite subtle and complex. For example, travelers' demand response depended on risk perceptions, and these varied across countries. At the same time, marked changes were already taking place in the industry, for instance, industry-wide restructuring and a number of high profile bankruptcies, so that it proved difficult statistically to distinguish the 9/11-effect from these other developments. Two years later Liu and Zeng (2007) used annual aggregate industry data obtained from the Air Transport Association of America and Airsafe.com to estimate demand models for U.S. airlines. The use of annual data does rather limit their model's ability of picking up shock effects, if any, of 9/11. The authors find that increases in fatality rates do tend to reduce the demand for air travel but that the 9/11-related increase in fatalities does *not* explain all of the subsequently observed fall in air travel. A different path is taken by Rupp, *et al*. (2005). They examine airline schedule recoveries after U.S. airport closures and find the resulting flight outcomes difficult to explain.

Guzhva (2008) uses a technique known as intervention analysis to assess the impact of 9/11 on U.S. airline industry performance. While he finds an initial effect strong enough to justify the federal government's subsequent financial support of the industry, he also suggests that the long-term effects were considerably smaller than the short-term ones and that the airlines were not equally affected. In particular, he finds that the pricing of airline stocks was much less accurate for smaller airlines than for larger ones. In a similar vein, a number of papers consider the stock market effects, for example Gillen and Lall (2003), who examine the reaction of airline share prices following 9/11.

Overall, the impact of 9/11 on the industry does appear unprecedented, but there is in fact no clarity over how it has affected airline demand. The event created some fear of flying, to be sure, but also led to the introduction of more rigorous security measures at airports, which by themselves may have reduced travel demand. Passengers could have moved to "safer" airlines, so that non-U.S. international air travel may have benefitted. Because of such potentially offsetting responses to 9/11, its effect on global air travel demand, if any, is an empirical rather than theoretical question. The extant studies tend to find that 9/11 does not fully explain the subsequent decline in airline demand at the time. Moreover, measured effects appear to have been relatively short-term in duration.

The rather limited extent of the literature does mean that there is considerable scope for further work on the relation between violence (such as terror) and effects on the air travel market. The extant literature has tended to focus on the 9/11 incident alone rather than on wider measures of the overall security environment. Moreover, it tends to focus on the U.S. airline industry, not the global industry. And the studies have not considered individual airlines, which means that they cannot pick up either heterogeneity across airlines nor possible demand substitution effects from one airline to another or from one set of airlines (U.S.) to another (non-U.S.).

1.2 Our study: Data, novelty, limitations, and main findings

Given the summary picture captured in the literature and in Figures 1 and 2, it seems worthwhile to investigate in further detail what are the effects—if any—of (1) violence, (2) pandemics, (3) financial shocks, and (4) natural catastrophes on the global airline industry, specifically on international scheduled air traffic. Figures 1 and 2 do suggest that *specific* instances of large-scale violence, such as major terror events, may have a considerable impact on the industry and hence that the *general* level of actual or perceived security, pre- or post-9/11, might have lasting effects on the industry's performance. To learn whether this is the case and, if so, what the magnitude and relative importance might be, the research underlying this Report employs data purchased from the International Civil Aviation Organization (ICAO) on various indicators of airline performance and indicators of global terror events derived from the Global Terrorism Database (GTD). Control variables reflecting potential global adverse shocks to the airline industry, such as economic and financial crises, pandemics, and natural catastrophes, are included as well. Our analysis uses panel data, focusing on both the entire available sample of some 443 airlines as well as on a panel of the 20 largest passenger airline companies. In addition, a small number of exploratory case studies of selected top-20 airlines are undertaken as well (see Appendix C).

Our study is novel in several ways. It employs unique datasets (such as ICAO and GTD); it examines airlines beyond the United States; it includes measures beyond revenue-passenger kilometers (RPK); it studies the full sample of airlines (n=443), the top-20 airlines in terms of international scheduled passenger traffic, and also studies a selection of individual airlines; it employs data with monthly rather than annual frequency; and it employs far more sophisticated econometric methods than have been used to-date in the literature. Nonetheless, limitations abound and the research findings presented here are tentative. The two main accomplishments are to have worked up a statistically "clean" dataset and to have built a base model applied to selected aspects of terror and war events. Now that the basic dataset and panel model have been constructed, it should be fairly straightforward to assemble more disaggregated data on wars, pandemics, and natural catastrophes and to include them in other runs of the basic model.

We point out that we do not study airline financials. The reason for this is that while financial data are available, ICAO reports them at annual frequencies and in U.S. dollars. Annual data are not sufficiently fine-grained to pick up any potential transitory shock effects that in most cases would be expected to be of less than one year in duration. Reporting in U.S. dollars involves problems of exchange rate and purchasing power parity conversions. A non-U.S. corporation may well have been profitable in home currency terms but not in dollar terms, and vice versa. By way of illustration, Figures 3 to 6 show various financial measures for Korean Air (KAL), one of our top-20 airlines. All four figures are drawn to the same horizontal scale. Data are for 1973 to 2007, with missing data points in 1982, 1991, and 2005. ICAO reports dollar values in current U.S. dollars (USD). For comparability, we converted them into constant dollars with base year 2005. Figure 3 shows KAL's total revenue (RT) and expense (EX), in billions of constant USD. Evidently, the airline has experienced substantial growth over the years. The most dramatic shock occurs in 1997, possibly linked to that year's East Asian financial crisis. Adverse shocks, somewhat smaller in scale, also occur in 1990 and 2001. In principle, this could be linked to the buildup to the Persian Gulf war of 1991 and to 9/11 (in 2001). However, both periods were also recessionary periods, and to sort out whether violence or economy (if either) accounts for the revenue fall, one would need to employ a statistical test. However, with only 32 data points at hand, there are too few observations from the point of view of statistical inference, especially as one needs to account for a number of potential confounding factors.

Figure 4 breaks KAL's revenue into its three reported constituents, revenue gained from passengers and baggage, freight and mail, and other (all also in constant 2005 USD). The 1990 revenue drop is revealed as one due to freight and "other," the 1997 decline is mostly due to a fall in passenger revenue, and the 2001 decline is due in

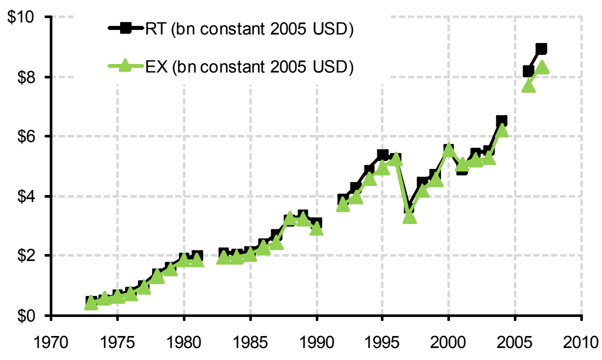

Figure 3: Korean Air (KAL); total revenue and expense. *Source*: Compiled from ICAO.

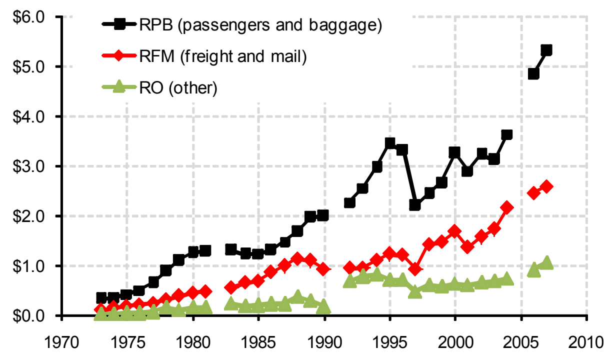

Figure 4: Korean Air (KAL); revenue components. Source: Compiled from ICAO.

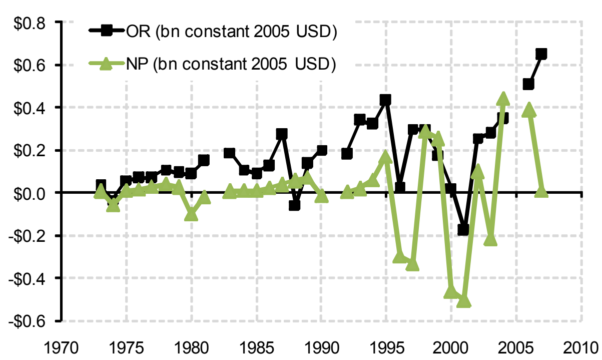

Figure 5: Korean Air (KAL); operating results/net profit. Source: Compiled from ICAO.

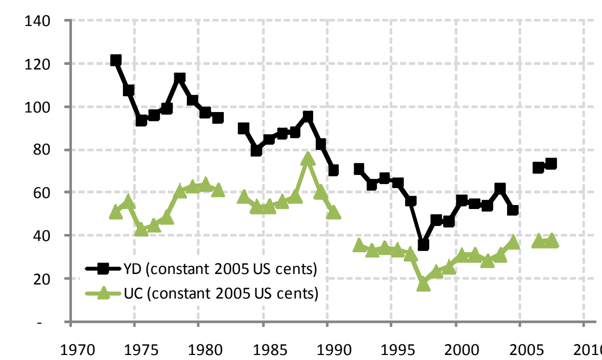

Figure 6: Korean Air (KAL); yield and unit cost. Source: Compiled from ICAO.

equal parts to passengers and freight while "other" stayed constant. A comparison of 1990, 1997, and 2001 is important because while an event such as 9/11 may keep passengers away, it would not necessarily keep freight off the airplanes. At any rate, as may be seen in Figure 5, operating results (revenue minus expense) already declined in the three years prior to 2001, and net profits were as sharply negative in 2000 as they were in 2001. Moreover, it is not clear just which financial measure to examine, in part because these are, statistically speaking, *endogenous* to (dependent on) the problem to be investigated: that is, airline management of course will react to market events and that reaction itself may change the parameters of interest. Finally, Figure 6 displays, for KAL, two standard industry measures called yield and unit cost. Yield is measured as passenger revenue per kilometer flown, and unit cost is measured as cost per available seat kilometer (whether the seat is filled or not). For KAL, yield declined constantly from 1973 to 1997, the low point, before turning around smartly. Neither 9/11 nor the 2003 Iraq war had any visually obvious effect. For a stretch of years, unit cost held roughly even at 60 cents/km, then fell through 1997, and since then rose again. Once more, there is no visually obvious effect of 9/11 or the Iraq war. ICAO does not provide a cost breakdown, for example into aircraft capital cost, labor cost, and fuel cost.

In sum, while from a business perspective it is understandable that one may wish to study the financials, there are both theoretical (endogeneity) and practical (small number of usable data points) problems with this approach. We therefore focus not on dollars, but on numbers of passengers and kilometers flown. This permits us to construct global air traffic demand equations that avoid the endogeneity problem, with the additional and necessary advantage of being able to employ monthly observations and therefore greatly enlarging the number of usable data points.

With this important clarification, our findings regarding global air traffic demand suggest that the natural catastrophe variable is irrelevant to *global* air traffic demand as such catastrophes are primarily local or regional events. The pandemic variable (SARS) is never relevant at a global level either. It turns out that, statistically, SARS acts more like an epidemic variable through its effects on airlines in Asia only. The economic and financial variables exert complex effects: For the top-20 airlines, international scheduled air traffic measured in *absolute* terms (number of kilometers and passengers flown) are not affected by unemployment but are affected by a fall in the S&P500 index, whereas *relative* air traffic measures (actual passenger and weight loads relative to airlines' passenger and weight load capacities) are affected by unemployment and a rise in the S&P500 index. However, for the full sample of all 443 airlines, unemployment does significantly affect international scheduled air traffic, even for the absolute measures. Finally, in regard to measures of terror and war-related violence—having accounted for the potential confounding factors—the one-off 9/11-event is fairly consistently relevant for about half of the top-20 airlines and also, statistically, for the entire 443-airline sample, as is the Iraq war. In contrast, the Persian Gulf war appears to have affected only a handful of the top-20 airlines. We observe considerable statistical mingling of the effects of specific shocks on specific airlines that, once amalgamated into the two larger samples (top-20 or all 443 airlines) appear to signal results that may be statistical artifacts: Building up a large sample from rather diverse individual airlines may yield misleading results.

Section 2 presents selected descriptive data obtained from the International Civil Aviation Organization (ICAO) regarding international scheduled passenger airline traffic and Section 3 presents data on transnational terror events obtained from the University of Maryland's Global Terrorism Database (GTD). Section 4 discusses control variables and data issues with ICAO and GTD. Section 5 illustrates the ICAO data with the example of data for Air Canada. Section 6 presents our model and econometric method. Sections 7 and 8 present the statistical results of our initial model runs with respect to the top-20 airlines and with respect to all 443 airlines in the sample. Section 9 considers absolute versus relative measures of airline performance, for example, the effect of terror events on air kilometers flown (absolute kilometers) versus the effect on the passenger load factor (the ratio of passengers flown relative to available seats). Section 10 considers size effects, meaning not statistical significance per se but the estimated magnitude of the effect of the relevant factors on airline performance. Section 11 concludes, followed by endnotes, references, and appendices.

2. Trends in international scheduled passenger airline traffic

We purchased and processed data from the International Civil Aviation Organization (ICAO), an organization of the United Nations system.[3] Purportedly, the data cover monthly traffic-related statistics for all ICAO member airlines in the world, with records for some airlines going back several decades.[4]

Although in some model specifications we include a weight carried variable (cargo traveling with passenger aircraft), on the whole we focus on understanding the monthly passenger volume of international scheduled airline traffic rather than on domestic flights or on nonscheduled (e.g., chartered) flights or on airfreight carriers' traffic (such as FedEx, UPS, or the cargo subsidiaries of the major passenger airlines). The reason for focusing on passenger volume is that this may help us, at least as a first approximation, to isolate factors that may influence passenger airline demand. Because airlines can countermand fluctuations in passenger volume with pricing, studying airline revenue is not a modeler's first-choice approach to studying the industry: In that case, one would be studying the industry's reaction to changes in underlying demand rather than studying the demand itself.[5] In addition, the choice of focusing on the volume variable is also dictated by the data, in that airline financials are available on an annual basis only, whereas the nature of the problem we study—the effect of violent events on passenger demand—generally involves single-day episodes that cannot be expected to affect airline traffic across the whole of a year, and, depending on the specific event, may not even affect them over the whole of a month.

Table 1: Top-20 passenger-carrying airlines by total revenue, 2007

ICAO code	*Country name*	*Airline name*	*Revenue (USD '000)*
AAL	US	American	22,832,757
UAL	US	United	20,049,094
DAL	US	Delta	19,238,800
AFR	France	Air France	18,406,565
BAW	UK	British Airways	15,849,992
KLM	Netherlands	KLM	14,987,414
JAL	Japan	Japan Airlines	14,810,371
COA	US	Continental	14,105,361
NWA	US	Northwest	12,734,621
ANA	Japan	All Nippon Airways	11,449,938
UAE	UAE	Emirates	10,453,470
QFA	Australia	Qantas	9,989,385
KAL	S. Korea	Korean Air	9,486,371
AWE	US	US Airways	9,317,637
SIA	Singapore	SIA	8,442,120
ACA	Canada	Air Canada	7,985,812
IBE	Spain	Iberia	7,133,477
SAS	Sweden	SAS	5,925,206
THA	Thailand	Thai Airways	5,675,516
LFH	Germany	Lufthansa	n/a

Source: Complied from ICAO data files.
Note: Southwest Airlines (United States) and Cathy Pacific (Hong Kong) were excluded because of limited traffic data records. Lufthansa (Germany) was included despite the lack of financial records.

The total number of airlines in the ICAO dataset is n=443. We applied our models both to all 443 airlines in the dataset and also to only the top-20 passenger-carrying airlines by total 2007 revenue (Table 1). Because of data gaps—airlines not reporting for every month of operation—it is not possible to construct a consistent passenger traffic profile across all airlines across all months and years in the ICAO dataset and, for total airline traffic, we therefore have to take IATA's numbers as given (Figures 1 and 2). Despite this drawback in regard to the display of descriptive ICAO data, it is however possible to statistically adjust for missing data and carry the inferential analysis forward. Moreover, it is possible to construct ICAO-based traffic information for the top-20 airlines as they tend to report data more reliably, i.e., with fewer missing observations.

3. Trends in transnational terror events

3.1 The ITERATE database

During the decade of the 2000s, events of domestic and transnational terrorism have received increased public attention. On account of frequent suicide bombings, 9/11, Madrid, London, Bali, Mumbai, and other terror actions ascribed to "Islamic fundamentalist" terror organizations, the world would seem to be a much less safe place than before, with bombings, hostage takings, assassinations, and threats and hoaxes occurring daily. But data collected for the ITERATE database and analyzed by our colleagues Walter Enders and Todd Sandler shows considerable variation within these categories and also shows that transnational terror events have been declining since their peak at the end of the Cold War-era (Figure 7).

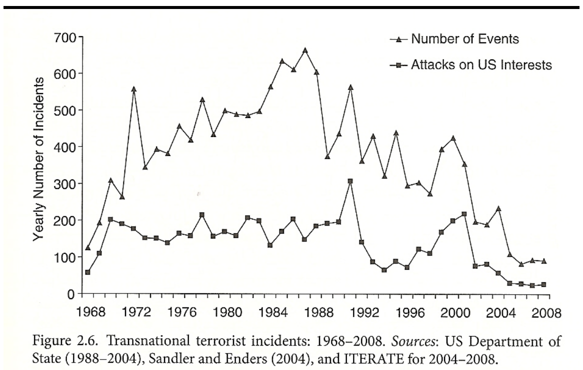

Figure 7: Number of transnational terror events.
Source: Enders and Sandler (2012, p. 49).

For transnational attacks on U.S. interests, the pattern is different. Throughout the 1970s and 1980s, attacks on

U.S.-related targets were fairly steady in number, at around 200 per year. A peak occurred in 1991, presumably related to the Persian Gulf war. Thereafter, terror events declined rapidly and rose again as from the mid-1990s, culminating in another peak in 2001 and a substantial decline since then.

Studying the detailed data (not shown here but available in Enders and Sandler, 2012), one finds that bombings drive the total incidence figures, with clear cycles related to international incidents. From the mid-1970s to late 1980s, terror organizations often seemed content with what amounted to acts of sabotage, damaging or destroying physical assets or causing other economic damage, without necessarily wounding or killing people. With the end of the Cold War, however, the proportion of lethal incidents has been rising. Figure 8 shows deaths and overall casualties (wounded and killed) from transnational terror events. The difference between deaths and casualties are those wounded in attacks. In the 1990s, even as the total number of casualties declines, the difference between deaths and casualties shrinks, implying that even as terror incidents became less frequent, its victims were more likely to die. In the early 2000s, that trend continued and, in the first part of the decade, was exacerbated by a renewed rise in the number of incidents as well.

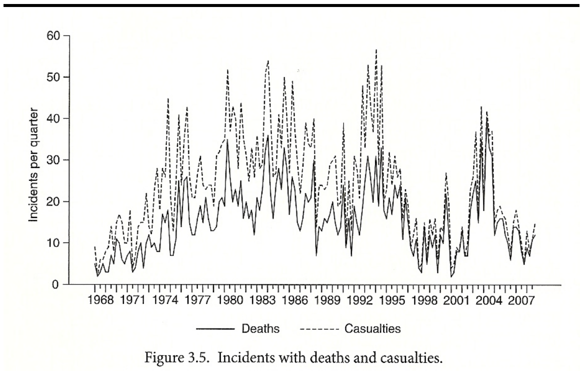

Figure 8: Quarterly number of transnational terror events; deaths and casualties (wounded and killed). *Source*: Enders and Sandler (2012, p. 74).

In terms of the geographical distribution of incidents and casualties, the West has seen a marked reduction, particularly Europe, whereas Asia has experienced a recent spike, and the Middle East has seen a massive increase in incidents. Of course, this may affect airline traffic, but perhaps more in routing decisions than in the number of overall air kilometers flown as tourists, especially, can easily substitute between potential locations to visit.

Data for the incidents recorded in Figures 7 and 8 rely in the main on newspaper accounts, which may not necessarily be fully complete and consistent in coverage. They do not contain much information on government strategies and behavior during incidents. Not all terror-related data is public, and inevitably there will be missing values.

Nonetheless, empirical analysis has found that the number of attacks is highly volatile over time and geography, with increased incidence during economic downturns and elections. Peaks correspond to particular international events, e.g., the 1972 Munich Olympic Games and the 1991 Persian Gulf war. As noted, attacks have become more lethal, and there has also been a change in the dominant motivation, from ideological to religious, with a related increase in suicide bombing and transnational attacks since the 1967 Yom Kippur war. Targets are frequently rich, Western countries but it is not clear at all that democracies suffer disproportionately.

Time-series analysis has identified trends, cycles, and occasional structural breaks in the transnational terror data series, providing some support for analyses which treat terror organizations as acting as if they were rational agents (that is, attempting to maximize the effect of their activities subject to budget, manpower, and other constraints). Research has identified substitution as well as income effects. For example, theory predicts that a terror organization would engage in high-risk, high-payoff activity less often than in low-cost, lower-payoff events: Logistically complex and hence costly hostage takings are expected to occur less frequently than cheaper bombings. This is confirmed by the empirical record.

Previous research has found no significant impact of 9/11 on the United States economy in the aggregate (Figure 9). By September 2001, the U.S. economy was already in recession (as from March that year), and the recession

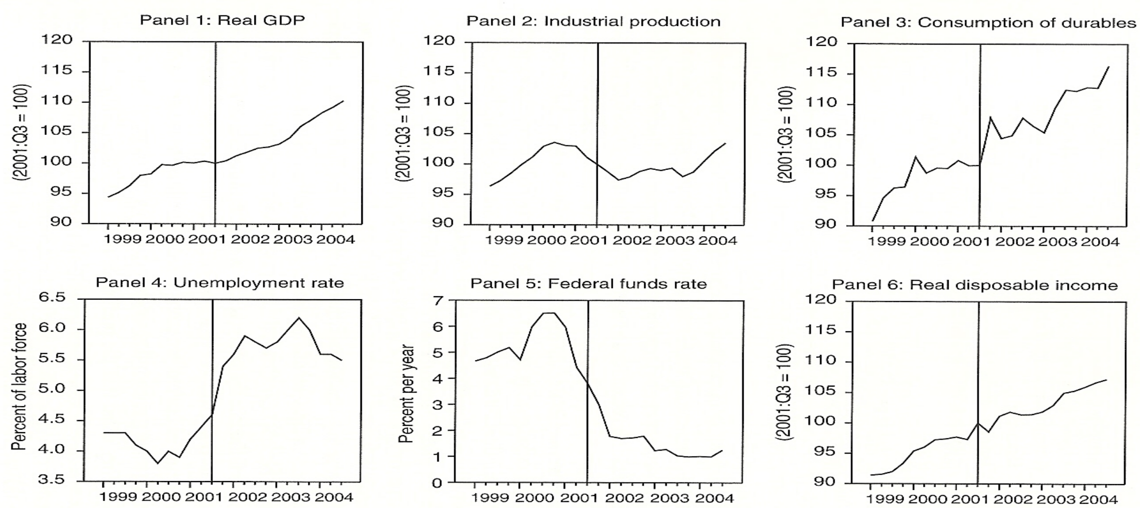

Figure 10.1. Macroeconomic variables and 9/11.

Figure 9: 9/11 and the U.S. economy.
Source: Enders and Sandler (2012, p. 296).

ended in November that year. Inflation-adjusted GDP and consumption had already stalled, industrial output declined, and unemployment risen. The Federal Reserve Board of Governors had already lowered market rates to help stimulate an economic recovery. The regional effect on output in the city of New York, and the effects on specific industries, such as insurance or financial services, of course would be expected to be higher, and there is diverse empirical evidence to this effect. In the aggregate, however, the effect of 9/11 on the U.S. economy was small, almost negligibly so, and certainly smaller than the economic effects of other conflicts such as the Iraq war.

Although empirical evidence points to the presence of primarily short-term effects borne by specific geographic regions and economic sectors on account of terror events, there can still be important long-term and aggregate costs,[6] especially if poor countries are targeted. (Nonstate) terror events can also affect government policy, especially if it leads to big increases in security spending and follow-on wars (the “War on Terror” and the Iraq war in the case of the U.S.), but the overall, worldwide aggregate economic effect of terrorism tends to be relatively small.

3.2 The Global Terrorism Database (GTD)

For our purposes, the ITERATE database, on which the discussion in the previous subsection is based, suffers from one crucial shortcoming: It focuses on transnational terror. On first sight, this may seem entirely sufficient for a study of international scheduled passenger air traffic; however, domestic terror attacks in Egypt (Cairo), India (New Dehli), Norway (Oslo), Spain (Basque country), or the United States (Oklahoma City, Oklahoma), may affect international scheduled passenger air traffic as well and so it seemed important to also obtain data on domestic terror.

The University of Maryland provided us with its Global Terrorism Database (GTD) of, at the time, over 87,000 coded domestic and transnational terror events worldwide, by month, January 1970 to December 2008, but with the monthly data for 1993 missing. An aggregate figure for 1993, however, was available, and we estimated the monthly data for 1993 using a statistical procedure. Figures 10 and 11 display the original GTD data, in monthly and annual format, respectively. The number of recorded events rises continuously from 1970 to 1991 (end of the Cold War),

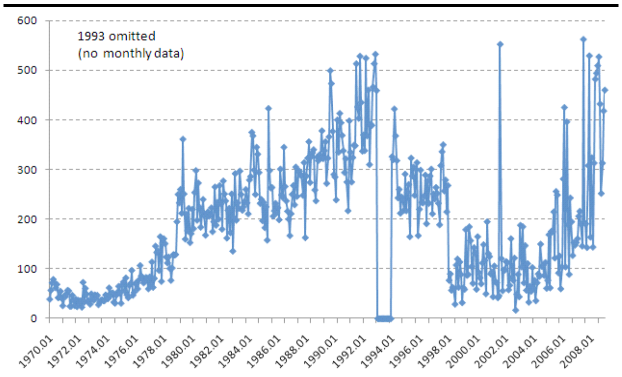

Figure 10: Monthly number of total domestic and transnational terror events, 1970:1 to 2008:12. *Source*: University of Maryland, Global Terrorism Database.

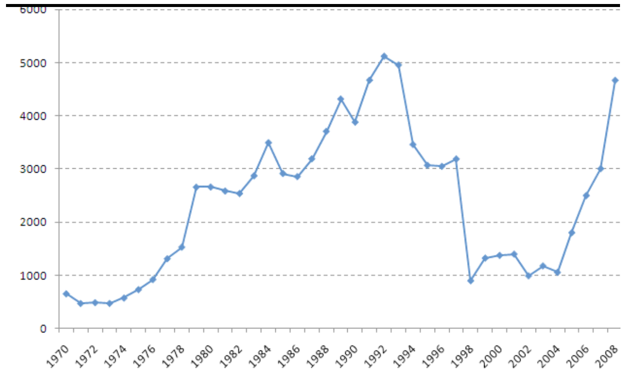

Figure 11: Annual number of total domestic and transnational terror events, 1970 to 2008. *Source*: University of Maryland, Global Terrorism Database.

then declines drastically through 1997, holds about even until 2003, after which it rises (coinciding with the start of the Iraq war). When comparing Figure 7 with Figure 11, note that the vertical scale of the former goes up to 600 (for the yearly number of transnational terror events) whereas the latter (for all events, domestic and transnational) goes to 6,000. Thus, domestic terror events are roughly an order of magnitude larger than are transnational ones.

4. Control variables and data issues with ICAO and GTD

As mentioned, data were purchased from the International Civil Aviation Organization (ICAO) in 2009. These are monthly airline traffic data. Contrary to expectations, severe data access, data processing, and data quality problems were encountered. Data cleaning took many months of time to perform. For example, some airlines had no ICAO code which hindered automated data sorting, itself necessitated by the very large database of some 370,311 observations. This was mainly a problem with smaller airlines, but also with some larger ones. Some airlines had multiple responses, in the sense of more than one set of data for a single airline; this is linked to corporate failures, takeovers, and mergers, and in some cases resulted in redundant data being left in the ICAO dataset. Some airlines had records that aggregated a number of months and failed to provide individual monthly data, for example, giving an aggregate figure for January to March instead of three monthly figures. Some airline records contained no data for a particular time period at all. We also found variations in the length of time series available for different airlines. And some of the variables of interest had a limited number of observations relative to other variables. All these and other problems had to be laboriously identified and addressed and, in the end, reduced our ultimate usable sample size.[7] We then analyzed the full, cleaned dataset for all 443 airlines but also to use a panel dataset for the top-20 airlines that provided the most reliable data.

The Global Terrorism Database (GTD), likewise, is not free of problems. First, while it codes over 87,000 terror events, recording some 200,000 killed and a further 245,000 injured victims of terror attacks, it does not distinguish between domestic and transnational events. Moreover, given the variables in GTD and the coding criteria employed, there is no immediately obvious way to effect such separation ourselves.[8] GTD is a daily events database and the over 87,000 cases had to be recoded even to generate the monthly and annual totals given in Figures 10 and 11. Second, there is no simple way to sort the database and extract data according to characteristics that might be of interest for the specific purpose of our study. For example, one would expect that the Madrid train bombing of 11 March 2004 might have affected all international airlines—not just, say, Iberia—flying scheduled service to and from that city. But in GTD, this day is in fact coded as six separate events. The perpetrators are identified as the Abu Hafs al-Masri Brigades, and on the face of it, it is not clear whether this is "domestic" or "transnational." In fact, it is not even clear that the group actually exists or ever existed.

In the event, proceeding on the assumption that both the *overall* number of terror events and the magnitude of the mayhem caused affect general airline demand more than does any *specific* event, location, and magnitude, we focused on including the *total* number of terror incidents, victims wounded, victims killed, and the number of total casualties (wounded or killed).

The method of analysis is to investigate the possible relation between various measures of airline traffic and a set of terror indicators. The indicators for airline traffic are (1) aircraft kilometers flown (ak), (2) number of passengers carried (pc), (3) passenger load factor in percent (plf), and (4) weight load factor in percent (wlf). The load factors are *actual* passenger and weight traffic measured as a percentage of available *capacity* to carry passengers and weight. These four measures—ak, pc, plf, and wlf—are hypothesized to be influenced by measures of terror activity: number of incidents (inc); number wounded (wound); number killed (kill); and number of casualties (casualties) [that is, wounded or killed].

Security-related factors other than incidents of terror may shock demand for the global airline industry as well, and for this reason binary variables were constructed for the 1991 Persian Gulf war, the 9/11 terror event, and the 2003 Iraq war. That is, we code one especially prominent terror event as well as two nonterror violent events, prominent wars. In addition, nonsecurity-related factors may drive changes in airline performance as well, such as changes in the world economy. To account for economic factors as control variables for airline passenger demand—that is, to estimate the effects, if any, of terror on airline demand apart from economic fluctuations—our preference would have been to employ some measure of output such as monthly GDP data. However, while some countries report quarterly gross domestic product (GDP) data, none report monthly. Instead, monthly unemployment rates—commonly used as a measure of economic health in such situations—were collected from the Organization for Economic Cooperation and Development (OECD). Available as from January 1980 for the countries that provide the bulk of international air travel, these data were added to the dataset. The U.S. unemployment rate was used as an indicator of changes in *world* airline demand. When unemployment is high in the U.S., this usually means that both the United States and the world economy are in recession. However, for the case studies, where available we used the unemployment rates for the country in which the specific case study airline is headquartered, for instance French unemployment rates in the case of Air France.

Unemployment is our proxy for the general business cycle, either globally or for specific countries. However, financial shocks—such as Wall Street's Black Monday in October 1987, the Asian financial crisis that began in July 1997 in Thailand, or the bursting of the "dot com" bubble in the U.S. as from March 2000—may also have adversely affected passenger airline demand, and not only for business travelers. Thus, while our empirical strategy was to use unemployment rates as a measure of routine business cycle movements to capture the general business climate (earned-income effect), we employ information based on the S&P500 index to capture financial shocks (wealth effect). Specifically, if monthly changes in the S&P500 index exceeded +/-10%, we coded the corresponding month as a shock, not unlike our coding of the 9/11 terror event and the two wars.

With respect to natural catastrophes, these can be very deadly and costly in property and lives affected and in the consequent insurance payouts. But they share a distinguishing characteristic in that they all are localized events, for instance the tsunami in Aceh, Indonesia, in 2004; the Kashmir earthquake in Pakistan, 2005; Hurricane Katrina in New Orleans, 2005; Cyclone Nargis in Burma, 2008; or the tsunami and earthquake in Fukushima, 2011. Because they are localized events, it is not likely that they much affect either *world* airline demand or *worldwide* demand for the top-20 airlines, especially since they tend to occur more frequently in regions that are economically poor and underserved by air transport (and rescue services) to begin with. Volcanic eruptions may affect air *routes* more directly—because of their potential to inject large quantities of debris into high-altitude air traffic corridors—but do not necessarily affect air *travel* per se. Severity of volcanic eruptions is measured by the Volcanic Explosivity Index (VEI), a combination of plume height and debris volume, and is similar in conception to the more familiar Richter scale for earthquakes: The higher the number, the greater the activity. The Mount Pinatubo eruption in June 1991 in the Philippines for example was a VEI-6 event, the largest volcanic eruption in air-travel history; the Mount St. Helens eruption in Washington state in the USA in March 1980 was a VEI-5 event; and the Mount Eyjafjallajökull eruption in Iceland in March 2010 was a VEI-4 event and led to the disruption and closure of a good bit of European airspace for a period of weeks. Still, these are unlikely again to affect either *world* demand or *worldwide* demand for any of our top-20 airlines. For these reasons, we examined but decided not to include variables related to natural catastrophes in our models.[9]

The Severe Acute Respiratory Syndrome (SARS) pandemic is a different matter, however. Even though the death toll was small, the news media attention given to the outbreak and the behavioral response that followed may well have affected air travel demand. The Centers for Disease Control and Prevention (CDC) in Atlanta, GA, USA, and the World Health Organization (WHO) in Geneva, Switzerland, list a number of severe pandemic outbreaks: For example, a Hong Kong flu in 1968/69 is estimated to have killed one million people worldwide. The effect on air travel demand, if any, will come through news media amplification such as was the case for the SARS pandemic threat which lasted from November 2002 to July 2003. While the list of *epidemics* is long and while these might have regional effects, *pandemics* today are few a number and are, with rare lapses such as SARS, mostly threats that are quickly handled via CDC/WHO. We therefore coded only the SARS outbreak in our dataset. (The H1N1 outbreak in 2009 lies outside our time frame of 1980-2007 applied to the full sample and to the top-20 sample.)

The SARS outbreak completely overlapped with the combat phase of the Iraq war (20 March to 1 May 2003). Potentially, econometric estimates could falsely attribute adverse global or airline-specific airline demand to the Iraq war that might in fact have been due to SARS. Entering both variables in the dataset permits us to separate their effects, in any, in spite of their overlapping time frames.

In all this, one must exercise great care statistically not to overfit potential explanatory factors to the data. A danger is that statistical "explanations" may become so closely linked to the particular data at hand that the general applicability of the results to future adverse demand shocks may be lost.

5. An illustration: Air Canada

To get an idea of the nature of the air traffic data, consider Air Canada, one of the world's top-20 airlines based on annual revenue in 2007 (Table 1). With a complete record of monthly data available, January 1980 to June 2009, the blue line in Figure 12 shows air kilometers flown (ak) per month over the sample period, and is measured on the left-hand side (LHS) scale. Starting in 1980, month 1, the data yields information regarding trend (long-term) and seasonality (monthly variation). The trend was mostly stable in the 1980s and early 1990s, followed by considerable growth into the early 2000s. Upon close inspection, two shocks appear visually evident, namely 11 September 2001 and the start of the Iraq war in March 2003, which in both cases were followed by quick recovery and then growth again, although with higher seasonal volatility. This suggests nonlinearities and perhaps a structural break for the post-9/11 time period. But various financial crises—for instance in 1987 and 1997—also appear to generate traffic volatility. The number of passengers carried (pc), measured on the right-hand side (RHS) scale in the same figure, shows a similar pattern.

The passenger load factor (plf), the blue line in Figure 13, measures revenue-paying passengers carried as a percentage of seat kilometers available (ska). The higher the load factor, the more passengers or the lower the ska. Again, strong seasonal effects can be observed, along with an initial trend increase and then decline, before fairly

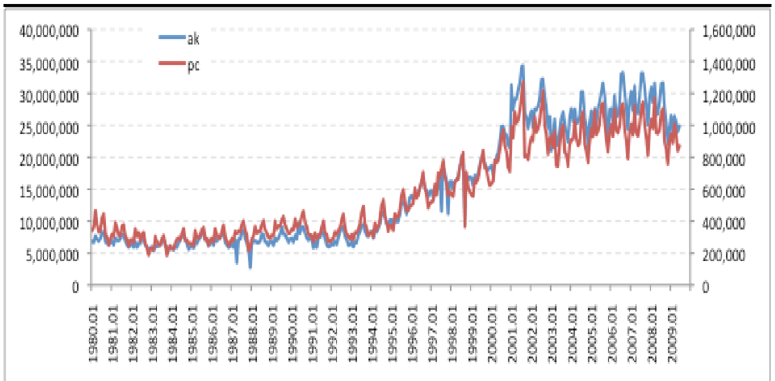

Figure 12: Air Canada. Air kilometers flown (ak—left-hand side scale) and passengers carried (pc—right-hand side scale).
Source: Compiled from ICAO.

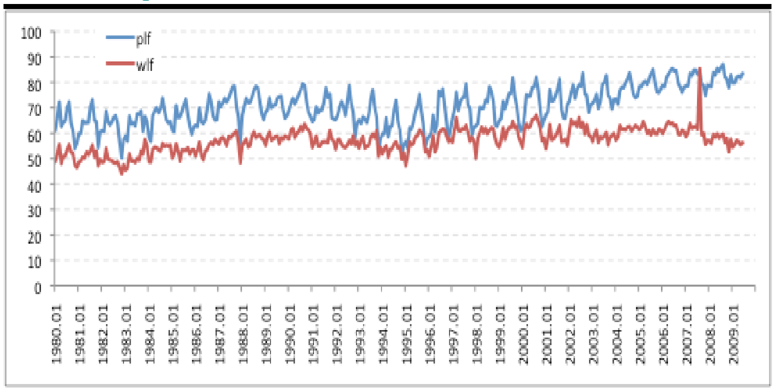

Figure 13: Air Canada. Passenger and weight load factors (plf; wlf), in percent of available seat/weight capacity.
Source: Compiled from ICAO.

consistent growth in the 1990s and 2000s with declining volatility. There is little—if any—visually obvious evidence of a 9/11-effect or of war effects. The weight load factor (wlf), the red line in Figure 13, is the load percentage of all weight carried (passengers, freight, mail) relative to load capacity. Only a single spike, in August 2007, can be observed. Seasonality prevails, although in the 2000s with far less volatility than in earlier decades.

All of the Air Canada time series show evidence of seasonal effects and are generally trended, that is, nonstationary. To better spot aberrations from trend and seasonality, the four panels in Figure 14 show the same four variables—ak, pc, plf, and wlf—with two mathematical transformations: First, the logarithm of each variable is taken and, second, the difference between the logarithms is computed from one month to the next. All series should then fluctuate around zero, as in fact they do. The spikes in the four figures correspond to unusually large fluctuations in the monthly data series. In all panels of Figure 14, the green-colored vertical bars refer to S&P500 movements of +10% (1982/09; 1991/02; 1998/10; and 2009/04); the red-colored bars to -10% movements (1987/10 and 11; 2001/09; 2002/07; and 2008/10). The grey-colored bars refer to the Persian Gulf war months of August 1990 to February 1991, the 9/11-event (shaded as September and October 2001), and the Iraq war months (February and March 2003), which are completely overlaid by SARS (November 2002 to July 2003), shaded in yellow color. There is little to suggest that the potential shocks due to violence (terror and war) much affected demand for Air Canada's services.[10] Only for the passengers carried and for passenger load factor does 9/11 coincide with a downward deviation from zero that appears large. But in the former case, *every* September in *every* year results in a drop of between 0.1 and 0.3 (and in one case of 0.8), so that a large part, and perhaps the better part, of the September 2001 drop is simply post-summer travel seasonality. In the latter case, there are about 10 other downward deviations that are equally large, or larger, that are not associated with any of our coded shocks. It is thus no foregone conclusion at all that 9/11 affected Air Canada's passengers carried or passenger load factor.

6. Model and method

In much of the literature researchers estimate a reduced form of a demand model which takes account of security issues, in a manner similar to the literature on demand for military expenditure for example. Estimation equations for

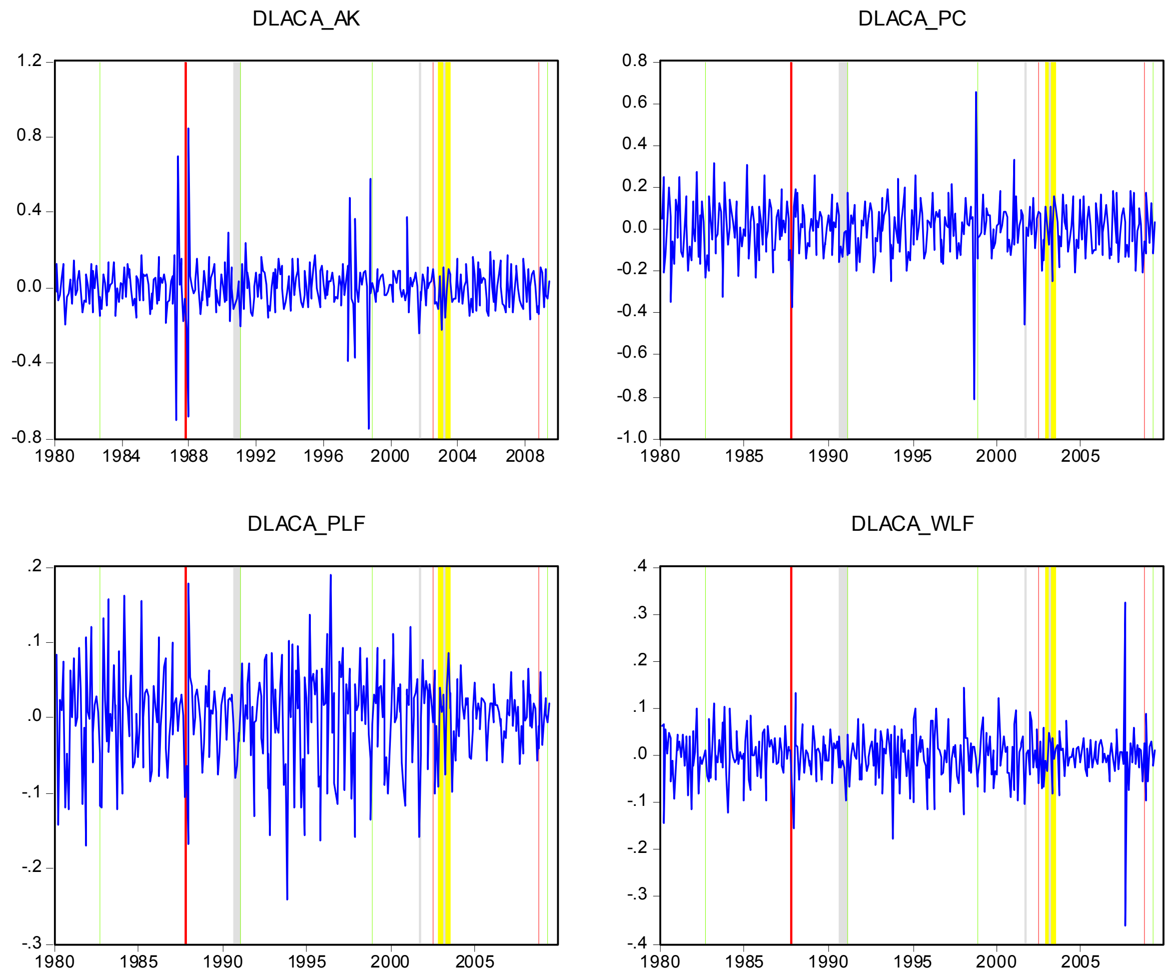

Figure 14: Air Canada, January 1980 to June 2009. Top-left: air kilometers flown; top-right: passengers carried; bottom-left: passenger load factor; bottom-right: weight load factor. All measured in differenced logarithms.
Source: Compiled from ICAO.
Note: See text for explanation.

the empirical analysis, where the demand for air services (denoted here as Q) is a function of economic resources, threats to security, and political factors, such as the nature of domestic and international regulation, may be written as

(1) $Q = D(Y, PQ, PO, Z, T)$,

where Y is income, PQ and PO are the prices of air services (Q) and other products (O) relative to an income deflator, Z is a vector (set) of demographic variables, and T of a vector of strategic variables. In general, prices are ignored, and a reduced form model is estimated, often after converting the variables into logarithmic form

(2) $y_t = \alpha_0 + \alpha_1 s_1 + \beta_1 x_t + \epsilon_{1t}$,

where s are the strategic variables of interest, including some form of 9/11-binary variable, and x are the conditioning variables, both economic and political. In this type of study, using high-frequency data there are a limited number of variables available across countries. For this reason, researchers often use whatever reasonable cross-country data are available. For example, U.S. unemployment can be used as a proxy for the state of general demand in the U.S. and the world economy.

It is necessary to allow for some form of dynamics as airline performance measures are trended over time and as it is possible that past airline performance is influencing future performance. It is also possible that the security and performance variables are themselves having a lagged (delayed) effect. To allow for all this, a general dynamic log-linear model was estimated of the form

$$(3) \qquad y_t = \alpha_0 + \alpha_1 s_t + \alpha_2 s_{t-1} + \beta_1 x_t + \beta_2 x_{t-1} + \gamma_1 y_{t-1} + \epsilon_t ,$$

which can be reparameterized as:

$$(4) \qquad \Delta y_t = \alpha_0 + \alpha_1 \Delta s_t + \alpha_2 s_{t-1} + \beta_1 \Delta x_t + \beta_2 x_{t-1} + \gamma_1 y_{t-1} + \epsilon_t .$$

This is the specification that is used in our empirical analysis.

So far the specification has been for a single airline, and this can be generalized to consider a panel of airlines simultaneously:

$$(5) \qquad \Delta y_{it} = \alpha_0 + \alpha_1 \Delta s_{it} + \alpha_2 s_{it-1} + \beta_1 \Delta x_{it} + \beta_2 x_{it-1} + \gamma_1 y_{it-1} + \epsilon_{it} .$$

A central issue in the choice of estimator is the relative size of N and T, the number of airlines and the number of months used in the analysis, respectively. The traditional panel literature deals with cases where N is large and T small, maybe only two or three time periods. Asymptotic analysis is done by letting $N \Rightarrow \infty$. In contrast, the time-series literature deals with the case where T is large and N small and asymptotics let $T \Rightarrow \infty$. Recently, there has been interest in panel time-series such as ours where both N and T are of the same orders of magnitude and asymptotics let both $N \Rightarrow \infty$ and $T \Rightarrow \infty$ in some way. What estimators are appropriate in the three cases differs. Define the country and overall means as

$$(6) \qquad \overline{m}_i = T^{-1}\sum_{t=1}^{T} m_{it} \, ; \overline{m} = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} m_{it} \ .$$

The total variation in the dependent variable (Q) is the sum of the within-country variation and the between-country variation, written as

$$(7) \qquad \sum_i \sum_t (m_{it} - \overline{m})^2 = \sum_i \sum_t (m_{it} - \overline{m}_i)^2 + T\sum_i (\overline{m}_i - \overline{m})^2 \ ,$$

and similarly for the regressors (Dunne and Smith, 2007).

The main panel estimators differ in how they treat the “within” and “between” variation. Ignoring the simple cross-section analysis, the estimators include the pooled Ordinary Least Squares (OLS) coefficients which combine the series, giving the "within" and "between" variations equal weight, and uses least squares on

(8) $m_{it} = \alpha + \beta' x_{it} + u_{it}$,

where β is a (k x 1) vector of slope coefficients. The fixed effects or "within" estimator allows intercepts to differ across countries but constrains the slopes to be the same:

(9) $m_{it} = \alpha_i + \beta' x_{it} + u_{it}$.

A two-way fixed effects estimator additionally permits the intercepts to vary by year, thus allowing for a completely flexible trend, or unobserved common factor, which affects each airline by the same amount:

(10) $m_{it} = \alpha_i + \alpha_t + \beta' x_{it} + u_{it}$.

A random-effects estimator assumes that slopes are identical and intercepts are randomly distributed, independently of the regressors. It calculates the optimal combination of within and between variations under these assumptions and is more efficient (makes better statistical use of the data) than the fixed effects estimation.

Finally, the random coefficient model (RCM) allows all the parameters to differ across countries,

(11) $m_{it} = \alpha_i + \beta_i' x_{it} + u_{it}$,

and calculates weighted averages of the individual time-series estimates, $\hat{\beta}_i$, the weights, W_{i} , being based on the variances of the $\hat{\beta}_i$ (see Pesaran and Smith, 1999).

A further issue arises with dynamic models since the within (fixed effect) estimator of

(12) $m_{it} = \alpha_i + \beta' x_{it} + \lambda m_{it-1} + u_{it}$

is consistent for large T, but is not consistent for fixed T, large N. In this case, the estimated coefficient of the lagged dependent variable is biased downwards (underestimated). This is the standard small-T bias of the OLS-estimator in models with lagged dependent variables. There are a variety of instrumental variable estimators for this case. However, if the true model is heterogeneous,

(13) $m_{it} = \alpha + \beta_i' x_{it} + \lambda_i m_{it-1} + u_{it}$,

and homogeneity of the slopes is incorrectly imposed, then the within-estimator is not consistent, even for large T. The coefficient of the lagged dependent variable is biased upwards (overestimated) toward unity (assuming the regressors are positively serially correlated, as is usually the case). The RCM estimator is, however, consistent for large T, although it suffers the small-T lagged dependent variable bias. Comparison of the various estimators, which are subject to different biases, can allow one to infer which biases are most important.

In the individual regressions,

(14) $m_{it} = \alpha_i + \beta_i' x_{it} + u_{it}$,

if the variables are integrated of order one, I(1), and also are cointegrated [the error term u_{it} is I(0)], then the least squares estimate of $\hat{\beta}_i$ gives a super-consistent estimate of the long-run effect for large *T*. However, as noted, if the variables are I(1) but are not cointegrated [the error term is also I(1)], then the estimated coefficients $\hat{\beta}_i$ do not converge to on the true but unkown β_i , as $T \Rightarrow \infty$, but to a random variable. The regression is then said to be spurious (misleading). Despite this, pooling or averaging over groups can allow one to obtain a consistent estimate of an average long-run effect from the levels regressions. Thus the pooled or average estimates from static levels regressions may be of interest even if individual airline equations differ and do not cointegrate (Dunne and Smith, 2007).

In what follows, we present and discuss first the results for the top-20 airlines in the sample, followed by those for the entire sample of 443 airlines.

Table 2: Top-20 airlines, monthly for 1980-2007

Dependent variable: Change in log of kilometers (*dlak*) flown

Independent variables	*var.*	*coeff.*	*t-value*
***Lagged log of kilometers flown**	***lak1**	**-0.204**	**-27.5**
Change in log incidents	dlinc	-0.001	-0.1
Log of incidents lagged	linc1	-0.002	-0.2
Change in log of U.S. unemployment	dluus	-0.188	-1.2
U.S. unemployment lagged	luus1	-0.015	-0.4
SARS	sars	-0.001	0.0
***S&P500 10% decline**	**drop10**	**0.086**	**2.7**
S&P500 10% increase	inc10	-0.008	-0.2
***Dummy for 9/11**	***d911**	**-0.062**	**-3.8**
Iraq war dummy	diraq	-0.01	-0.2
Gulf war dummy	dgulf	0.014	0.5
***Trend**	***ym**	**0.001**	**13.2**
Months (seasonality)	***s1**	**0.41**	**2.3**
	***s2**	**-0.81**	**-4.5**
	***s3**	**0.093**	**5.1**
	s4	-0.003	-0.2
	***s5**	**0.049**	**2.7**
	s6	0.014	0.8
	***s7**	**0.041**	**2.3**
	s8	0.021	1.2
	***s9**	**-0.049**	**-2.7**
	s10	0.031	1.7
	***s11**	**-0.046**	**-2.5**
***Constant**	***cons**	**3.112**	**22.7**

7. Analysis of panel of the top-20 passenger airline companies

Estimating the models for the panel of top-20 airlines using the logarithm of air kilometers flown (ak) as the dependent variable and total terror events as the indicator of terrorist threat (the "incidence" variable) gives the results summarized in Table 2. Values that are statistically significantly different from zero—are systematically rather than randomly related to kilometers flown—are indicated with an asterisk and set in bold typeface.

The results seem to suggest that the growth of demand for airline kilometers traveled is a function of the past level of demand (*lak1*), adverse changes in the S&P500 index (*drop10*), a one-time negative shock effect of the 9/11 attack (*d911*), an upward-pointing overall trend (*ym*), which captures things such as general population and average income growth, and a handful of seasonality variables (*s1*, *s2*, *s3*, *s5*, *s7*, *s9*, and *s11*) relative to December. Importantly, neither the number of terror incidents per se, nor the unemployment proxy or the wars or the pandemic variable (SARS) showed anything close to statistical significance. Moreover, the S&P500 variable is of the "wrong" sign, indicating that air travel demand would increase following a ten-percentage point or more drop in the index.

This is a rather unexpected result. But as demand and terror can be measured alternatively, a similar set of estimations were undertaken on the alternative measures. Results are reported in Table 3 where the variables marked by an asterisk and bold typeface are statistically significant, i.e., statistically different from zero. (For convenience,

Table 3: Top-20 airlines; results for different specifications

Aircraft kilometers (dlak)	*Passengers carried (dlpc)*	*Passenger load factor (dlplf)*	*Weight load factor (dlwlf)*
Block 1: by incidents			
*lak1	*lpc1	*lplf1	*lwlf1
dlinc	dlinc	dlinc	dlinc
linc1	linc1	linc1	linc1
dluus	dluus	dluus	*dluus
luus1	luus1	*luus1	*luus1
sars	sars	sars	sars
*drop10	*drop10	drop10	drop10
inc10	inc10	*inc10	*inc10
*d911	*d911	*d911	*d911
diraq	*diraq	*diraq	*diraq
dgulf	dgulf	*dgulf	*dgulf
*ym	*ym	*ym	ym
Block 2: by killed			
*lak1	*lpc1	*lplf1	*lwlf1
dlkill	dlkill	dlkill	dlkill
lkill1	*lkill1	*lkill1	lkill1
dluus	dluus	dluus	*dluus
luus1	luus1	*luus1	*luus1
sars	sars	sars	sars
*drop10	*drop10	drop10	*drop10
inc10	inc10	*inc10	*inc10
*d911	d911	*d911	*d911
diraq	*diraq	*diraq	*diraq
dgulf	dgulf	*dgulf	*dgulf
*ym	*ym	*ym	ym
Block 3: by wounded			
*lak1	*lpc1	*lplf1	*lwlf1
dlwound	dlwound	dlwound	dlwound
lwound1	lwound1	lwound1	lwound1
dluus	dluus	dluus	*dluus
luus1	luus1	*luus1	*luus1
sars	sars	sars	sars
*drop10	*drop10	drop10	*drop10
inc10	inc10	*inc10	*inc10
*d911	*d911	*d911	*d911
diraq	*diraq	*diraq	*diraq
dgulf	dgulf	*dgulf	*dgulf
*ym	*ym	*ym	ym
Block 4: by total casualties			
*lak1	*lpc1	*lplf1	*lwlf1
dlcasualties	dlcasualties	dlcasualties	dlcasualties
lcasualties1	lcasualties1	*lcasualties1	lcasualties1
dluus	dluus	dluus	*dluus
luus1	luus1	*luus1	*luus1
sars	sars	sars	sars
*drop10	*drop10	drop10	*drop10
inc10	inc10	*inc10	*inc10
*d911	*d911	*d911	*d911
diraq	*diraq	*diraq	*diraq
dgulf	dgulf	*dgulf	*dgulf
*ym	*ym	*ym	ym

we ignore the coefficient signs and also the 11 seasonal variables as they are not germane to the issues at hand here.) The first block of rows ("*by incidents*") relates four different demand measures (namely aircraft kilometers; passengers carried; passenger load factor; and weight load factor) to terror measured by the total number of terror incidents, so that the first column is a shortened version of Table 2.

In blocks 2, 3, and 4, the exercise is repeated except that the measure of terror is changed from the number of total terror incidents to the number of people killed in terror attacks, the number wounded in such attacks, and the total number of casualties on account of terror attacks (wounded and killed), respectively.

As already suggested, while the variables in the first set of rows do not seem to be able to explain airline demand as measured by the logarithm of the absolute indicators of kilometers flown (ak) or passengers carried (pc), they do seem somewhat more helpful in explaining the relative air travel measures, that is, passenger and weight load factors (plf and wlf, respectively). For example, in column 3, the growth in passenger load factor across the 20 airlines for our monthly data from 1980 to 2007 would appear to depend on (be explained by) system inertia (the lagged value of plf), by the lagged value of U.S. unemployment, by an increase in the S&P500 index, and by 9/11, the two wars, and the overall trend variable. At least at first sight, this appears to be a reasonable result.

Interestingly, the statistical results are perfectly consistent across the four blocks of rows: Regardless of which measure of terror is employed, in each case the models pick out exactly the same explanatory variables as statistically significant, or not. Moreover, the results are also perfectly consistent between the two absolute measures and the two relative measures of air traffic.

Table 4: Random coefficient model results, top-20 airlines

Change in log of kilometers flown	*Var.*	*#sig*	*Mean*	*St.Dev.*
Lagged log of kilometers flown	**lak1**	**17**	**-0.184**	**0.199**
Change in log incidents	dlinc	2	0.000	0.013
Log of incidents lagged	linc1	4	-0.003	0.022
Change in log of U.S. unemployment	dluus	7	-0.074	0.267
U.S. unemployment lagged	luus1	2	-0.005	0.091
Binary for SARS	dsars	1	-0.001	0.088
Binary for S&P500 10% decline	drop10	1	0.074	0.117
Binary for S&P500 10% increase	inc10	4	-0.003	0.101
Binary for 9/11	**d911**	**10**	**-0.056**	**0.101**
Binary for Iraq War	diraq	1	-0.023	0.067
Binary for Gulf War	dgulf	1	-0.001	0.039
Trend	**ym**	**15**	**0.001**	**0.002**

Note: Results of seasonal (monthly) variables not shown.

Table 5: Random coefficient model results, top-20 airlines, for other airline demand measures

	Killed			*Wounded*			*All casualties*		
	#sig	*Mean*	*Std*	*#sig*	*Mean*	*Std*	*#sig*	*Mean*	*Std*
lak1	**17**	**-0.178**	**0.197**	**17**	**-0.180**	**0.200**	**17**	**-0.180**	**0.199**
dlx	3	-0.003	0.020	1	-0.004	0.021	3	-0.004	0.024
lx1	2	-0.007	0.020	4	-0.001	0.021	4	-0.005	0.017
dluus	7	-0.094	0.241	6	-0.066	0.226	6	-0.079	0.228
luus1	3	-0.001	0.066	4	-0.010	0.085	3	-0.003	0.070
sars	1	-0.004	0.073	1	-0.001	0.088	1	-0.004	0.079
drop10	1	0.074	0.433	1	0.074	0.426	1	0.074	0.431
inc10	4	-0.003	0.119	5	-0.002	0.120	5	-0.003	0.120
d911	**10**	**-0.056**	**0.104**	**11**	**-0.057**	**0.110**	**11**	**-0.057**	**0.108**
diraq	1	-0.025	0.066	1	-0.026	0.068	1	-0.026	0.068
dgulf	1	-0.001	0.041	2	-0.001	0.042	2	-0.002	0.041
ym	**15**	**0.001**	**0.002**	**16**	**0.001**	**0.002**	**16**	**0.001**	**0.002**

Note: The "x" in dlx and lx1 stands for "killed," "wounded," and "all casualties" in the respective equations. Results of seasonal (monthly) variables not shown.

When we examined the results for individual airlines, rather than for the panel of all of the top-20 jointly, we found a considerable amount of heterogeneity among the carriers and to deal with this, the base model was estimated using a so-called random coefficient method. This involved estimating separate equations for each of the 20 airlines and then computing the mean of each of the relevant coefficients. The distribution of the means then provides the standard errors within which the true, but unknown, coefficients are expected to lie.

The results, shown in Table 4, are remarkably similar to the fixed-effect results (Table 2) with the coefficient on the lagged dependent variable close to -0.2, and significant for 17 of the 20 airlines. (The bolded lines in Table 4 do not indicate statistical significance; instead, they highlight those variables that are statistically significant for 10 or more of the 20 airlines, that is, for half or more of our sample.) Except for *drop10*, which had the "wrong" sign in Table 2, the same variables are significant, *dlak1*, *d911*, and the trend, *ym*. Moreover, the three statistically significant coefficients in Table 4 are identical in sign and very similar in magnitude to those of Table 2. From a statistical point of view, all this is somewhat reassuring.

Also in Table 4, the GTD data for the number of terror events per se add virtually no explanatory power to the number of airline kilometers flown for each of the top-20 airlines, 1980 to 2007. The only consistently significant security effect is the 9/11 event, yet even this is statistically significant for only just half of the top-20 airlines. (7 of the 20 are North American airlines.) Instead, airline demand as measured by air kilometers seems to be determined as an autoregressive process (that is, inertia) around a trend with seasonal dummies, with the odd shock specific to individual airlines and the more general impact of 9/11. This suggests that 9/11 was an aberration or, alternatively, that it takes an event as massive as 9/11 to shock global airline demand, as measured by aircraft kilometers flown.

Table 6: All airlines (*n*=443), monthly, 1980-2007

dlak	*coeff.*	*t-value*
***lak1**	**-0.239**	**-82.3**
dlkill	0.008	1.5
lkill1	-0.002	-0.4
***dluus**	**-0.114**	**-2.1**
luus1	0.021	0.8
sars	-0.004	-0.2
drop10	-0.040	-1.8
inc10	0.002	0.1
***d911**	**-0.025**	**-2.1**
diraq	-0.053	-1.8
dgulf	-0.026	-1.3
***ym**	**0.001**	**18.3**
***s1**	**-0.055**	**-4.2**
***s2**	**-0.133**	**-10.1**
***s3**	**0.044**	**3.3**
***s4**	**-0.036**	**-2.7**
s5	0.017	1.3
s6	-0.01	-0.8
***s7**	**0.047**	**3.5**
s8	-0.007	-0.5
***s9**	**-0.074**	**-5.6**
***s10**	**-0.033**	**-2.5**
***s11**	**-0.124**	**-9.4**
***cons**	**2.975**	**40.5**

Note: The interpretation follows Table 2.

Re-estimating the other variants of the model gives the results displayed in Table 5, which are consistent with the kilometers flown indicator: Only the 9/11 event appears relevant among the shock variables; everything else appears determined by inertia, trend, and seasonality factors. Although perhaps a surprising result, it is welcomed for its message of statistical consistency.

When the exercise of Tables 4 and 5 is repeated for passenger load factor (plf) rather than air kilometers (ak), the following variables are statistically significant for 10 or more of the 20 airlines: inertia (that is, lagged plf), lagged U.S. unemployment, a 10% increase in the S&P500 index, and the trend and seasonality variables. The 4 terror or 2 war measures are statistically significant only for between 6 to 8 airlines, never more than that. Economics trumps security. Once more, this result points to considerable heterogeneity in the sample of the top-20 airlines: As the Air Canada example (Figures 12, 13, and 14) already hinted, it appears that it may be inappropriate to lump rather diverse airlines into a single sample.

In what follows, we therefore examine not only the entire group of *n*=443 airlines in Sections 8, 9, and 10, but also conduct, in Appendix C, exploratory case studies of specific top-20 airlines.

8. Results for the total sample (all airlines, all years)

A procedure similar to that employed in Section 7 was followed for a panel that included all of the data that had not been excluded for reasons of inconsistency. Starting with the results for demand measured by air kilometers and terror measured, this time, by the number of people killed in terror events, gives the results in Table 6. Apart from prior month performance, trend effects, and seasonality, only the 9/11-event and the U.S. unemployment rate (as a proxy for the state of the world economy) affect the results.

Table 7 presents the results for the variations of the base model. As before (Table 3), it turns out that load factors (plf and wlf, respectively) are more affected by economic and political events than are either aircraft kilometers flown (ak) or the number of passengers carried (pc).

9. Absolute versus relative measures of air traffic demand

Aircraft kilometers flown (ak) and number of passengers carried (pc) are absolute measures of airlines' performance. In Table 7, these respond to a lag-indicator, to U.S. unemployment and either to 9/11 or to the onset of the Iraq war (but never the Gulf war). In contrast, the relative measures—passengers or weight carried as a proportion of available carrying capacity—respond to lagged dependent variable values, to a variety of economic indicators, and to several of the violence (terror and war) measures. However, they never respond, statistically, to SARS, to a drop in the S&P500 by 10 or more percentage points, or to the Gulf war.

A striking difference between Table 3 (top-20 airlines) and Table 7 (all 443 airlines) is that only in the case of

Table 7: Significant determinants for different model specifications for all airlines (*n*=443)

	Aircraft kilometers (dlak)	*Passengers carried (dlpc)*	*Passenger load factor (dlplf)*	*Weight load factor (dlwlf)*
Block 1: by incidents				
	*lak1	*lpc1	*lplf1	*lwlf1
	dlinc	*dlinc	*dlinc	dlinc
	linc1	linc1	*linc1	*linc1
	dluus	*dluus	*dluus	*dluus
	luus1	luus1	*luus1	*luus1
	sars	sars	sars	sars
	drop10	drop10	drop10	drop10
	inc10	inc10	*inc10	*inc10
	*d911	d911	*d911	*d911
	diraq	*diraq	*diraq	*diraq
	dgulf	dgulf	dgulf	dgulf
	*ym	*ym	ym	*ym
Block 2: by killed				
	*lak1	*lpc1	*lplf1	*lwlf1
	dlkill	*dlkill	*dlkill	*dlkill
	lkill1	lkill1	*lkill1	lkill1
	*dluus	*dluus	*dluus	*dluus
	luus1	luus1	*luus1	*luus1
	sars	sars	sars	sars
	drop10	drop10	drop10	drop10
	inc10	inc10	*inc10	*inc10
	*d911	d911	*d911	*d911
	diraq	*diraq	*diraq	*diraq
	dgulf	dgulf	dgulf	dgulf
	*ym	*ym	*ym	*ym
Block 3: by wounded				
	*lak1	*lpc1	*lplf1	*lwlf1
	dlwound	*dlwound	*dlwound	*dlwound
	lwound1	lwound1	*lwound1	*lwound1
	*dluus	*dluus	*dluus	*dluus
	luus1	luus1	*luus1	*luus1
	sars	sars	sars	sars
	drop10	drop10	drop10	drop10
	inc10	inc10	*inc10	*inc10
	*d911	d911	*d911	*d911
	diraq	*diraq	*diraq	*diraq
	dgulf	dgulf	dgulf	dgulf
	*ym	*ym	ym	*ym
Block 4: by casualties				
	*lak1	*lpc1	*lplf1	*lwlf1
	dlcasualties	*dlcasualties	*dlcasualties	*dlcasualties
	lcasualties1	lcasualties1	*lcasualties1	lcasualties1
	*dluus	*dluus	*dluus	*dluus
	luus1	luus1	*luus1	*luus1
	sars	sars	sars	sars
	drop10	drop10	drop10	drop10
	inc10	inc10	*inc10	*inc10
	*d911	d911	*d911	*d911
	*diraq	*diraq	*diraq	*diraq
	dgulf	dgulf	dgulf	dgulf
	ym	*ym	ym	*ym

the former is the Persian Gulf war variable statistically significant for the load factor variables. As mentioned in conjunction with the discussion of Tables 4 and 5, however, this effect is restricted to between 6 to 8 out of the 20 airlines. Likewise, the top-20 airlines (Table 3) also appear somewhat more affected by downturns in the S&P500 index, at least for the wlf measure, whereas all 443 airlines seem more affected by S&P500 upturns. Another striking difference between Tables 3 and 7 is that our measures of terror (incidents, wounded, killed, casualties) on the whole do *not* seem to much affect the top-20 airlines, but do appear to affect the entire sample of 443 airlines. In contrast, the SARS variable is never of importance, at least not in the joint samples. (SARS appears important for the Asian airlines—Japan Airlines, Korean, Qantas, Singapore, and Thai Airways—but this would need to be tested separately.)

To sum up to this point, we excluded on theoretical grounds natural catastrophe-related effects on international scheduled air travel demand (they are always localized effects). The tests we ran suggest that the pandemic variable (SARS) is never relevant at a global level either. SARS may act statistically more like an epidemic rather than a pandemic variable by exerting effects on specific airlines. The economic and financial variables (U.S. unemployment and S&P500 index) exert complex effects: For the top-20 airlines, absolute international scheduled air traffic measures (ak; pc) are not affected by unemployment but are affected by a *fall* in the S&P500 index, whereas relative air traffic measures (plf; wlf) are affected by unemployment (especially wlf) and a *rise* in the S&P500 index. However, for all 443 airlines, unemployment does significantly affect international scheduled air traffic even for the absolute measures. Finally, in regard to measures of violence (terror and war), the

Table 8: Top-20 airlines, monthly, 1980-2007

dlplf	*Coeff.*	*t-value*
***lplf1**	**-0.265**	**-32.0**
dlkill	0.001	0.6
***lkill1**	**-0.004**	**-3.0**
dluus	-0.042	-1.4
***luus1**	**-0.041**	**-6.1**
sars	-0.001	-0.2
drop10	-0.010	-1.6
***inc10**	**-0.061**	**-7.7**
***d911**	**0.018**	**6.1**
***diraq**	**-0.053**	**-5.9**
***dgulf**	**-0.020**	**-4.1**
***ym**	**0.000**	**3.4**
***cons**	**1.215**	**30.2**

Note: Seasonals omitted.

one-off 9/11-event is fairly consistently relevant for about half of the top-20 airlines but also, statistically, for the entire 443-airline sample, as is the Iraq war. The Persian Gulf war, again, appears to have affected only a handful of the top-20 airlines. In all this, we observe a statistically mingling of the effects of specific shocks on specific airlines that, once amalgamated into a larger samples, either the top-20 or all 443 airlines, appear to signal results for either of the two larger samples that may or may not in fact be justified: Building up a large sample from diverse individual airlines may just yield misleading results.

10. Size effects

To illustrate size effects, Table 8 records the specific coefficient estimates for the passenger load factor (plf) model for the top-20 airlines, with the number of people killed in terror events as the terror measure. (For convenience, the 11 monthly estimates have been omitted from the table.) In this model, various violence indicators and economic proxies are statistically significant (different from zero), suggesting that they do influence the passenger load factor, the share of passenger kilometers flown as a percentage of seat kilometers available. The dependent variable is the *change* in the logarithm of the passenger load factor (*dlpdf*).

The first significant factor is the prior-month logarithm of the level of plf (*lplf1*): The higher the prior-month plf, the more pronounced the percentage decline in plf to the next month, and vice versa. In other words, the more unusual any one month's aberration, the more the next month's plf is likely to get "pulled back" to trend. This effect is in addition to the overall rising trend (*ym*) itself and to seasonality effects (the s_i's, not shown in the table) and simply means that inertial forces are by far the overriding factors accounting for month-to-month passenger load factor changes in the ordinary course of the airlines' business. None of this comes as a surprise: The statistical estimation merely provides quantification of these effects (as well as a check on these intuitions).

The factors intrinsic to the airline business (inertia, trend, and seasonality) are amplified by external variables. The economic control variable—U.S. unemployment—is statistically significant but only in its "prior month" variant (*luus1*), that is, the influence of the prior month on the current month on the growth rate in air traffic (plf). A worsening unemployment number in any one month adversely affects changes in the growth rate in the passenger load factor in the follow-on month. This, also, is as expected. In contrast, the +/– 10-percentage point changes in the S&P500 index (*inc10* and *drop10*) do not appear to work well, statistically. The *drop10* variable has a negative coefficient, as might be expected, but is not statistically significantly different from zero. The *inc10* is statistically significantly different from zero, and strongly so, but has the "wrong" sign, suggesting that a drastic increase in the index reduces the plf growth rate that month. Although one can rationalize this result, it seems counterintuitive. The coefficient value, however, is small in size (-0.061) and in any case affects just a mere four months of data (1982:09; 1991:02; 1998:11; and 2009:04).[11] The SARS variable is statistically insignificant. As discussed, despite its pandemic classification, in effect it was an epidemic, primarily affecting the Pacific/Asian airlines in our sample and not showing an effect in the whole sample of the top-20 global airlines.

More important for our purposes, the growth in the passenger load factor in any given month is influenced in a statistically significant way by the number of people killed in prior-month terror events (*lkill1*). News carries, and news affects international scheduled air travel demand. "Statistically significant" means that the estimated effects are not likely to be due to chance (random) variation in the plf number but may truly be ascribed as causal effects of terror events on the airline business. As expected, the coefficient is negative, which means that an increase in the number of terror-related killings reduces the follow-on month growth rate in the passenger load factor, and vice versa (that is, fewer terror killings, higher load factors).

In a similar manner, the two wars (*diraq* and *dgulf*) exerted statistically significant adverse effects on passenger load factors for each month in which the wars were in the combat stage. Finally, the coefficient for the 9/11-event is strongly statistically significant but comes out with a *positive* sign. This may appear puzzling—why would 9/11 have led to an *in*crease in the plf growth rate?—but recall that the plf is the ratio of passengers carried to available seat capacity. Unquestionably, air kilometers traveled and passengers carried (pc) declined in response to 9/11 [the relevant coefficients from those models are –0.062 (t = –3.9), and –0.025 (t = –2.1)] but, as all travelers know, airlines responded by withdrawing aircraft from service, or using smaller aircraft, and packing their remaining aircraft with more passengers. In a word, efficiencies increased, as shown with rising passenger load factors. Upon individual inspection of the plf charts for each of the top-20 airlines (see Appendix B), it becomes clear, however, that increasing plf efficiencies are part of a long-term trend, particularly for the U.S.-based airlines, so that this 9/11-related effect is not visually apparent in an unambiguous manner. Only the statistical modeling and estimation reveals that such an effect appears to exist. However, at 0.018, the size of the coefficient is not overly large. It is, in fact, smaller than are the coefficients of the two wars.

In addition to these so-called short-term effects on month-to-month growth *rates*, the mathematics of the model permits one to derive long-term relationships in the data that determines the log-*levels* of plf. This can be computed by setting the log-level values equal to their lagged values, which makes the change variables equal to zero and drops out the lag-variables. With coefficients rounded to the third decimal place, and omitting the seasonal factors, the long-term relationship then may be written as

$$0 = -\,0.265\,lplf - 0.004\,lkill - 0.041\,luus - 0.001\,sars - 0.010\,drop10 - 0.061\,inc10 + 0.018\,d911 - 0.053\,diraq - 0.020\,dgulf + 0.000\,ym + 1.215. \tag{15}$$

Solving for *lplf* gives

$$lplf = 4.579 - 0.016\,lkill - 0.154\,luus - 0.006\,sars - 0.038\,drop10 - 0.230\,inc10 + 0.070\,d911 - 0.199\,diraq - 0.076\,dgulf + 0.000\,ym. \tag{16}$$

In Table 8, the interpretation is that the immediate, short-term effect of a 1% increase in the *growth* of the number of people killed in global terror events increased *growth* of the passenger load factor of our top-20 sample airlines by 0.001% (the statistically insignificant *dlkill* coefficient in Table 7), while over time (the long-term) every 1% increase in the *number* of people killed decreased the passenger load factor *ratio* by 0.016% (the *lkill* coefficient in equation 16).

Because the coefficients for *lkill* and *luus* in equation (16) both refer to percentage changes, they may be compared to each other. Thus, the effect of a 10% increase in the U.S. unemployment rate (for instance, from 5.0 to 5.5 percent) exerts an effect about 10 times as strong (0.154/0.016 = 9.625) than would a 10% increase in the number of people killed in terror events (for example, from 50 to 55). More important than killings per se are the event shocks: The Persian Gulf war reduced the passenger load factor for the top-20 airlines by about 0.08% per month of war. Similarly, the shock of the Iraq war was about -0.2% on plf. But both wars were short in duration.

11. Summary and conclusion

This project aimed to undertake a quantitative study of the effect, if any, of large-scale violence in the form of terror and war on global air traffic demand, while taking account of possibly confounding shock factors such as economic and financial crises, pandemics, or natural catastrophes. We excluded on theoretical grounds natural catastrophe-related effects on international scheduled air travel demand (they are always localized effects and cannot be expected to affect global air traffic demand). The first stage of the empirical work involved acquiring, processing, and analyzing ICAO data on airline travel demand indicators. This saw considerable practical problems and concern over the quality and consistency of the data on which a number of bodies and other researchers would appear to make rather bold aggregate claims. Likewise, we collected terror-related data. The ICAO data came to more than 370,000 observations; the terror data to more than 87,000 incidents. We added economic, financial, and other data as well.

Constructing panels of (clean) data produced seemingly reasonable results. The empirical tests suggest that the pandemic variable (SARS) is never relevant at a global level. SARS acts statistically more like an epidemic variable through its effects on airlines in Asia. The economic and financial variables exert complex effects: For the top-20 airlines, absolute international scheduled air traffic measures (ak; pc) are not affected by unemployment but are affected by a fall in the S&P500 index, whereas relative air traffic measures (plf; wlf) are affected by unemployment (especially wlf) and a rise in the S&P500 index. However, for all 443 airlines, unemployment does significantly affect international scheduled air traffic, even for the absolute measures. Finally, in regard to measures of violence (terror and war), the one-off 9/11-event is fairly consistently relevant for about half of the top-20 airlines but also, statistically, for the entire 443-airline sample, as is the Iraq war. In contrast, the Persian Gulf war appears to have affected only a handful of the top-20 airlines. We observe considerable statistically mingling of the effects of specific shocks on specific airlines that, once amalgamated into the two larger samples (top-20 or all 443 airlines) appear to signal results that may not in fact be justified: Building up a large sample from diverse individual airlines may yield misleading results.

Endnotes

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1. OAG (2011). The white paper consists of a series of charts with commentary that "eye ball" the effects, if any, of potentially adverse shocks. The paper contains no statistical analysis at all.

2. See, e.g., http://www.statcan.gc.ca/ and http://www.abs.gov.au/ [accessed 9 October 2011].

3. A data request made to IATA in late 2008 was not fulfilled.

4. The ICAO data also include annual finance-related statistics for airlines and for airports. As noted, apart from the considerable econometric disadvantage of using annual rather than monthly data (the availability of far fewer data points would lead to reduced statistical confidence in the estimated parameters of interest), airlines' financial results are subject to a number of factors beyond air traffic demand, for example jet-fuel prices, airport charges, and government regulations.

5. Likewise, we do not include fuel and labor costs, airport charges, regulatory burdens, and so on. All these are supply rather than demand factors and speak, in part, to the quality of airline management under adverse conditions rather than to the demand for the underlying service on offer.

6. For the United States, see, e.g., Yerger (2011).

7. To download, process, and clean the ICAO dataset of several hundred thousand data points in size cost us the better part of a year's work as well as the employment of 2 research interns for 3 months of time.

8. An attempt by Enders, Sandler, and Gaibulloev (2011) to through the GDT dataset of, at the time, 82,536 events led, first, to the exclusion of about 18,000 events as not meeting the definition of terror and, second, to the classification of a further 7,000 events as "unknown," leaving 46,413 domestic and 12,862 transnational events in their rendition of the GTD dataset.

9. When modeling demand for specific airlines in specific regions, however, it may well be appropriate to take account of natural catastrophes.

10. Formal Augmented Dickey Fuller tests showed all series—ak, pc, plf, and wlf—to be I(1), integrated of order one. To isolate factors other than time and seasonality, the series were detrended to make them stationary. The variables then were logarithmically transformed, differenced, and regressed on a time trend and on 11 monthly dummy variables, with December as the default month with respect to which the other months are measured. (The choice of the default month is arbitrary and does not affect the statistically analysis.) The time trends were not unexpectedly statistically insignificant. The plots of the regression residuals represent the growth in the variable (difference in logarithms) when time and seasonality have been taken into account. This means that one can be sure that any extreme values represent shocks rather than time and seasonality. For simplicity, in the main text we show only the plots of the series' differenced logarithms, rather than the residual plots. Both sets are very similar to each other.

11. One can rationalize in that a higher S&P500 may lead airline management to exuberantly increase capacity (denominator) even as passengers (the numerator) fail to show up immediately. Thus, the ratio, pfl, would fall (a negative coefficient). But this seems to stretch things more than warranted. It is possible that the S&P500 index is too U.S.-centric and that it might have been better to use a global equity index rather than a U.S. one. For now, it seems important that our model does include a control variable for economic wealth instead of just ignoring this possible channel of affecting air traffic demand.

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List of appendices

A: ICAO variable list and summary statistics
B: Top-20 airlines' air traffic measures
C: Indicative case studies

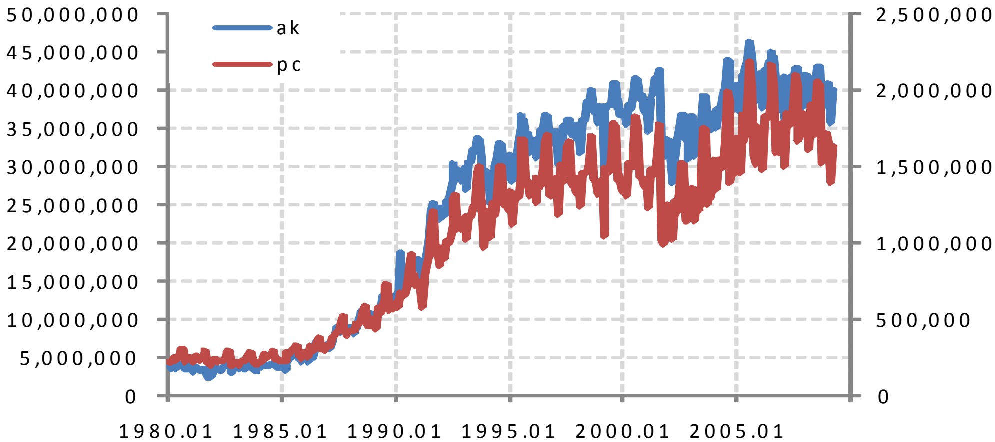
Appendix A: ICAO variable list and summary statistics

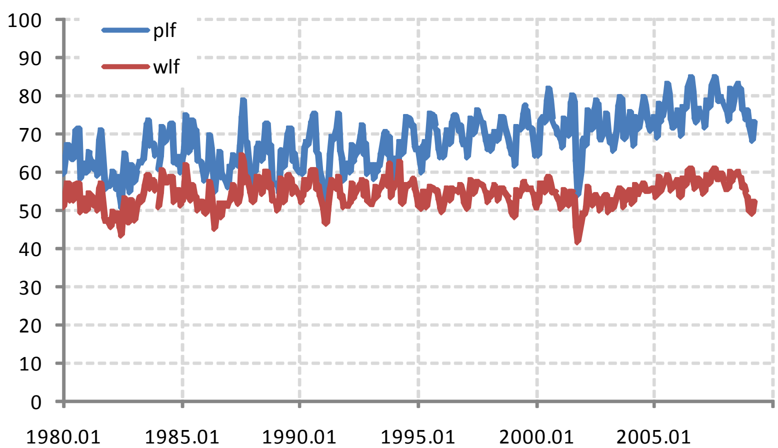
Var	*Name*	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
ak	aircraft kilometers ('000s)	259,750	2,208,134	7,884,990	0	4.03e+08
ad	aircraft departures	260,162	1,811.93	6,678.79	0	534342
ah	aircraft hours	369,419	2,420.616	9,926.108	0	675616
pc	passengers carried	190,669	194,799.2	741,904.5	0	5.76e+07
fc	freight tonnes carried	235,593	3,874.504	20,316.48	0	2289942
pk	passenger kilometers ('000s)	183,444	1.45e+08	3.16e+08	0	2.15e+09
ska	seat kilometers available ('000s)	180,980	1.78e+08	3.56e+08	0	2.15e+09
plf	passenger load factor	176,065	62.53101	18.09672	0	100
ttk	total tonne kilometers ('000s)	259,076	3.78e+07	1.29e+08	0	2.14e+09
ptk	pass. tonne kilometers incl. bag ('000s)	191,019	3.14e+07	1.06e+08	0	2.15e+09
ftk	freight tonnes kilometers ('000s)	138,932	2.43e+07	8.59e+07	0	5.48e+09
mtk	mail tonne kilometers ('000s)	124,280	1,212,466	4,186,880	0	2.50e+08
tka	tonne-kilometers available ('000s)	259,718	6.03e+07	1.97e+08	0	2.15e+09
wlf	weight load factor	234,468	55.26734	17.96506	0	100

All variables and data for international scheduled passenger service. Also see http://icaodata.com/Terms.aspx [accessed 10 September 2011]

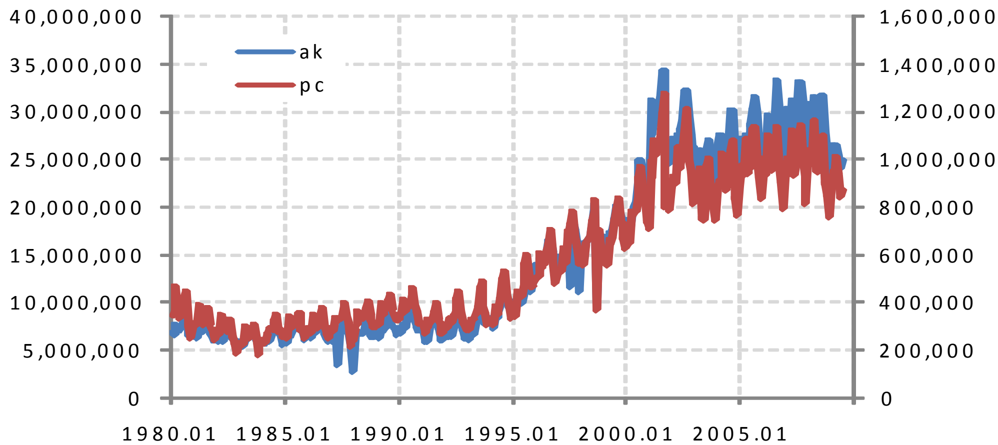
Appendix B: Top-20 airlines' air traffic measures

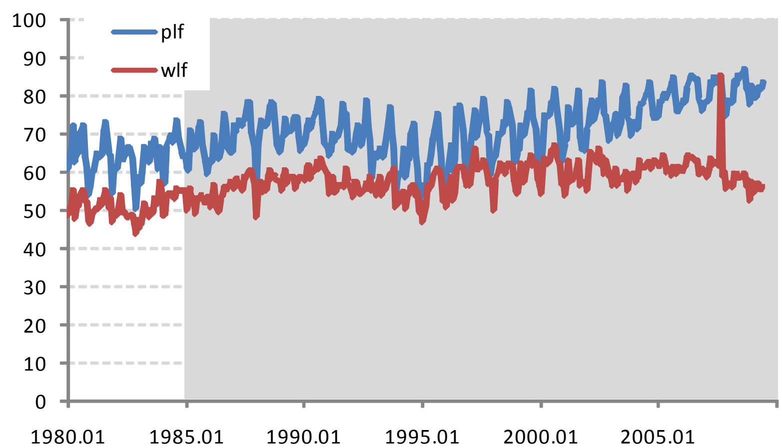
AMERICAN | ICAO code: AAL
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009





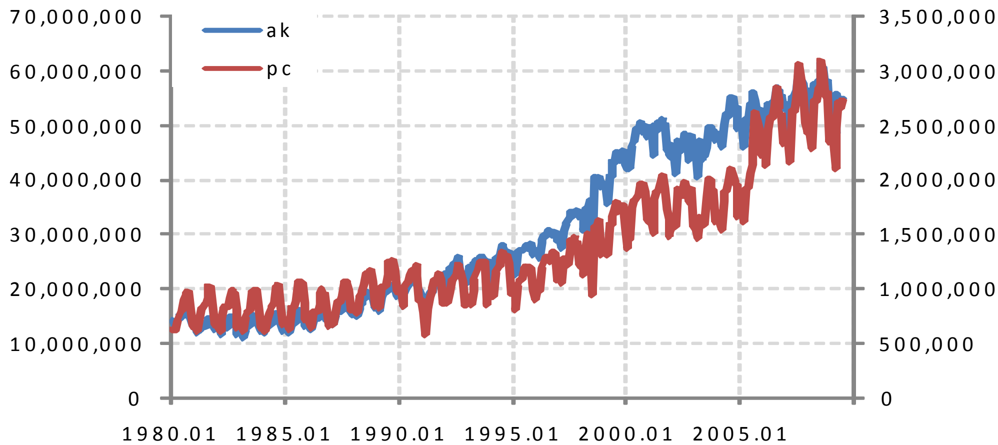
AIR CANADA | ICAO code: ACA
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

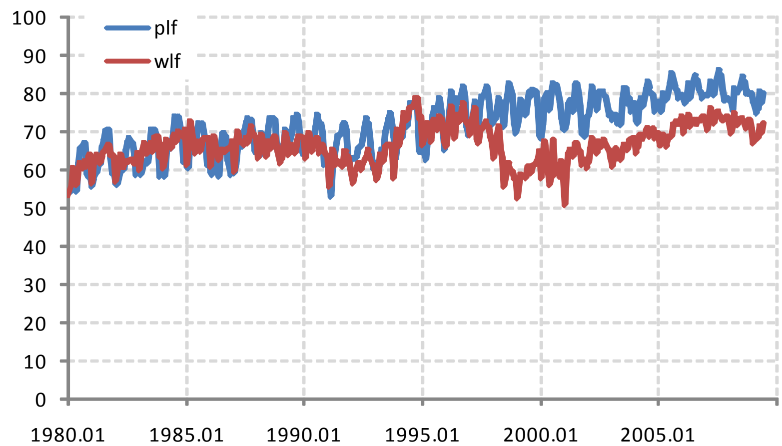




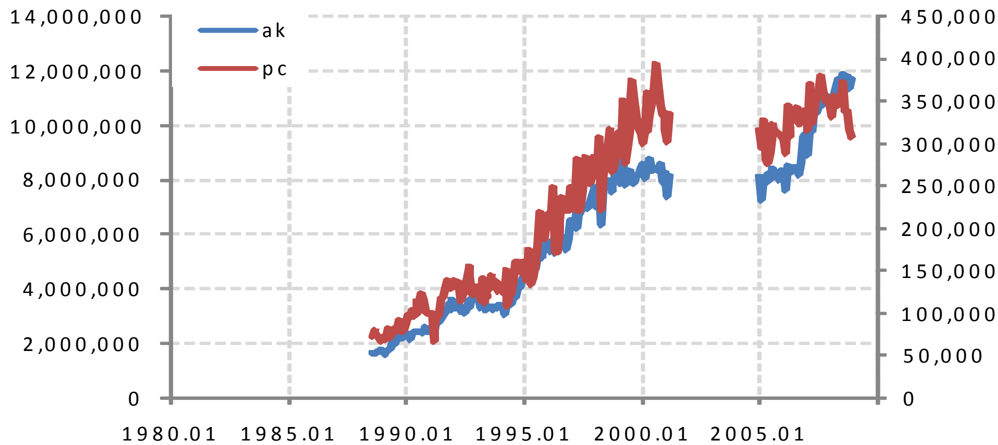
AIR FRANCE | ICAO code: AFR

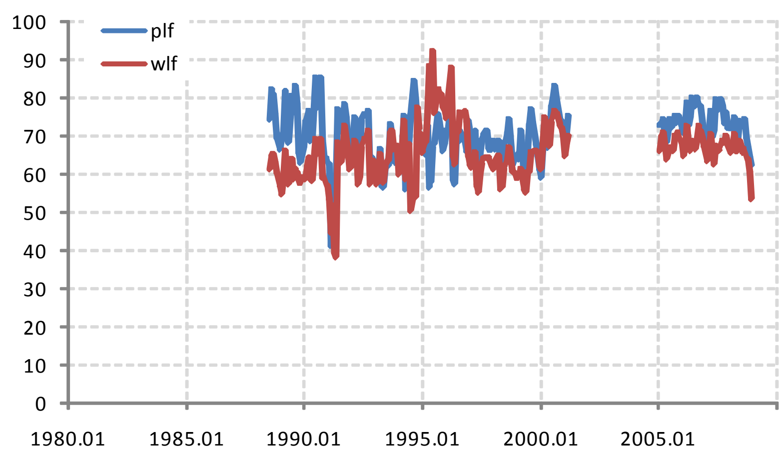
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009



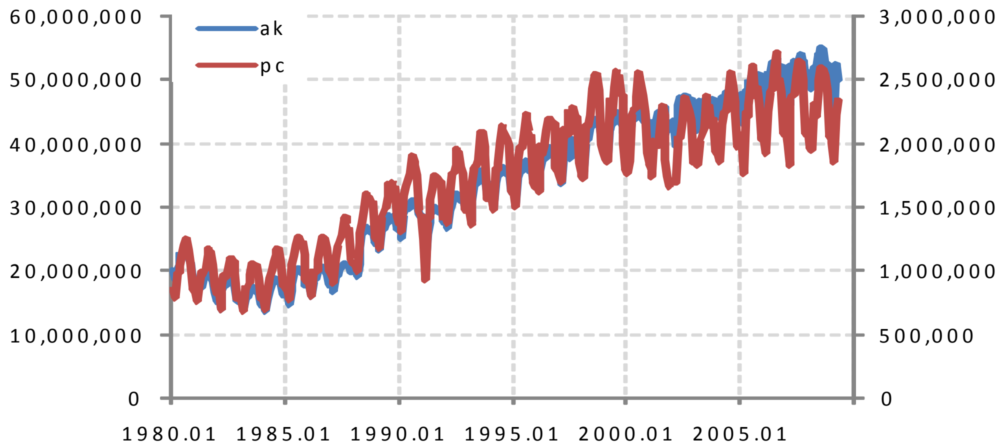


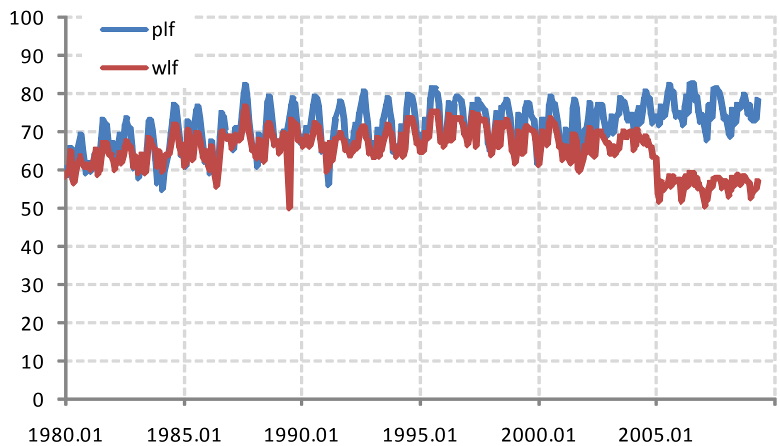
ALL NIPPON AIRWAYS | ICAO code: ANA
- Top panel: ak (LHS scale: kilometers flown in ‘000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009





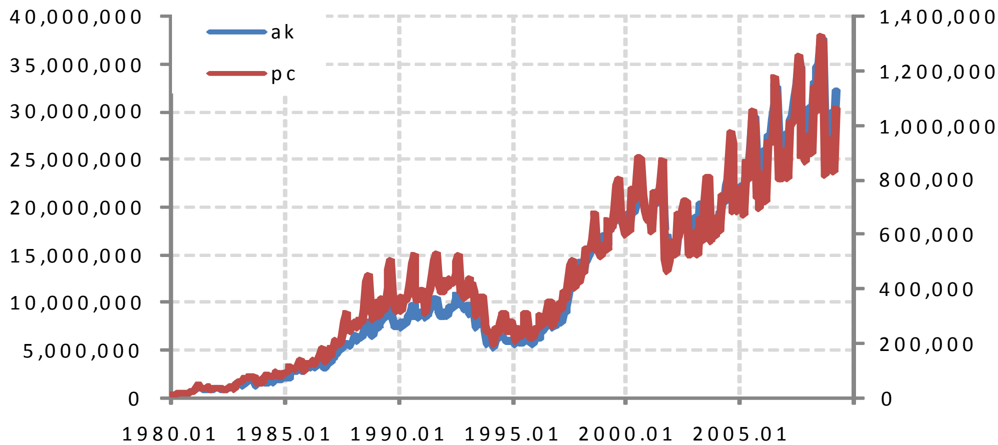
BRITISH AIRWAYS | ICAO code: BAW
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

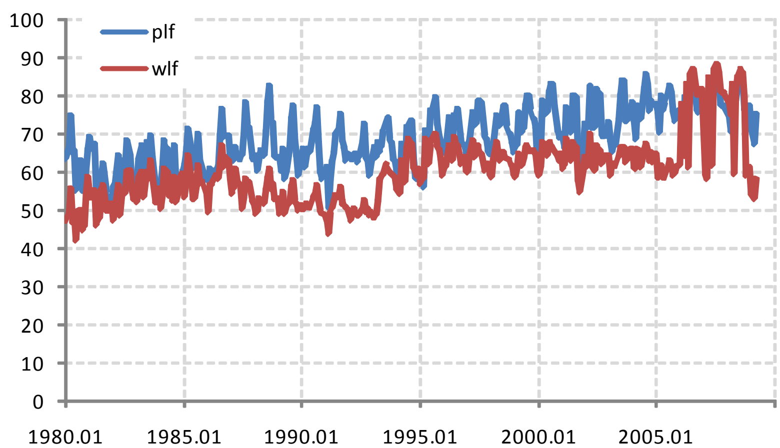




CONTINENTAL | ICAO code: COA

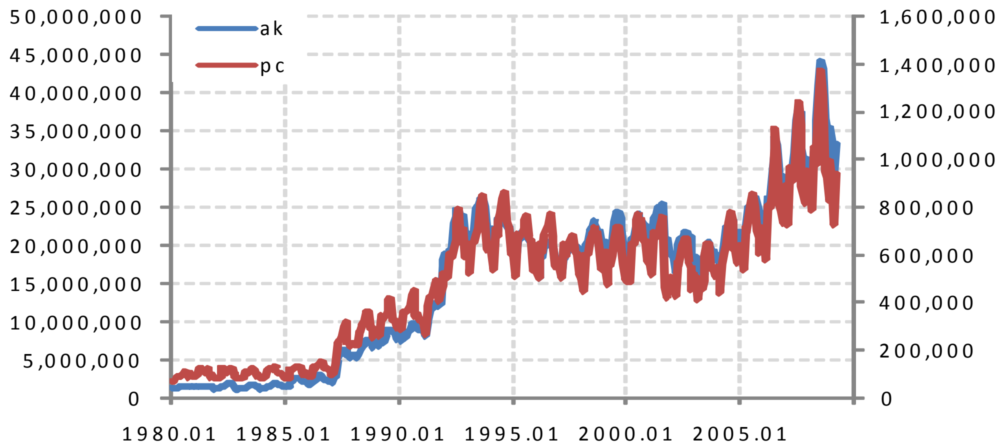
- Top panel: ak (LHS scale: kilometers flown in ‘000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

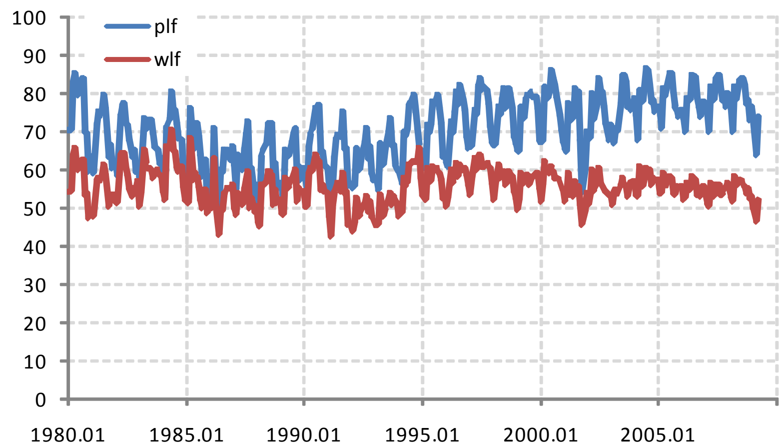




DELTA | ICAO code: DAL

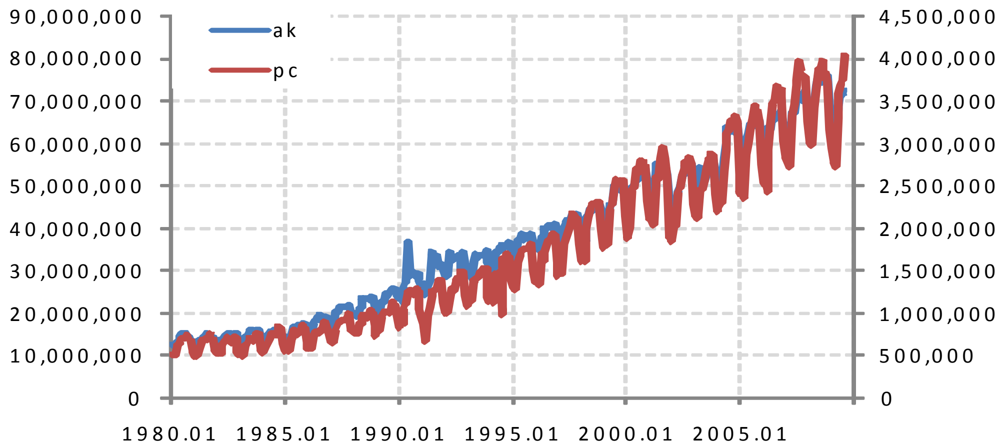
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

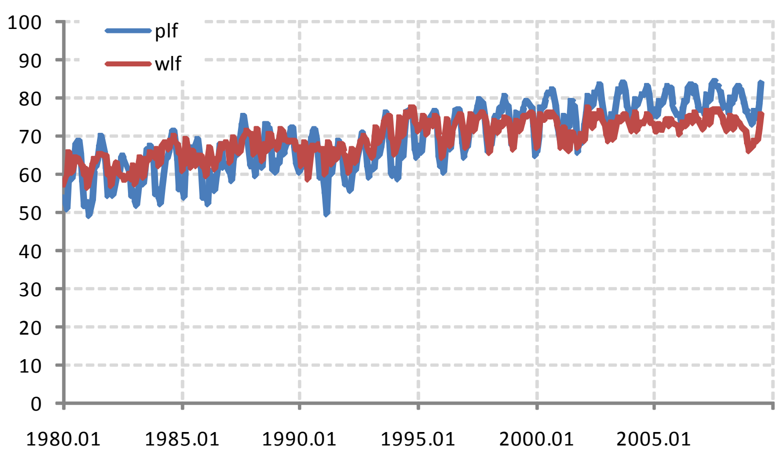




LUFTHANSA | ICAO code: DHL

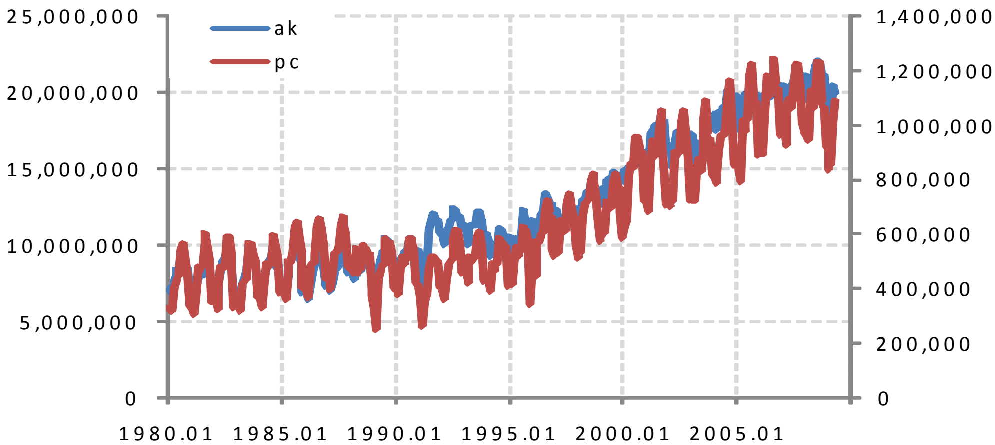
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

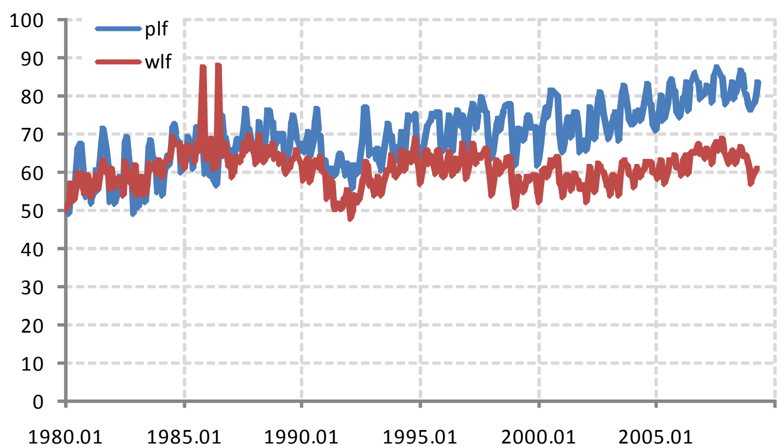




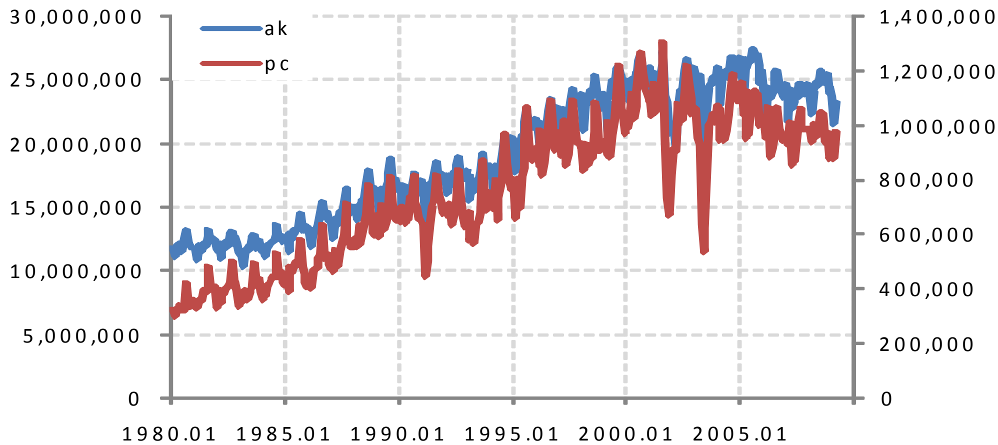
IBERIA | ICAO code: IBE

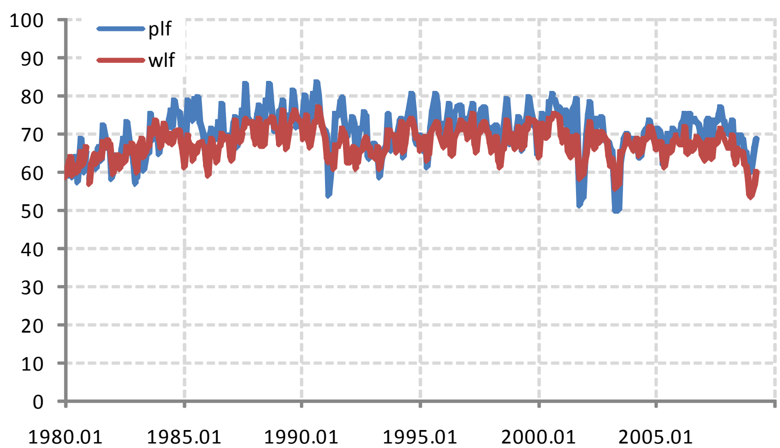
- Top panel: ak (LHS scale: kilometers flown in ‘000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009





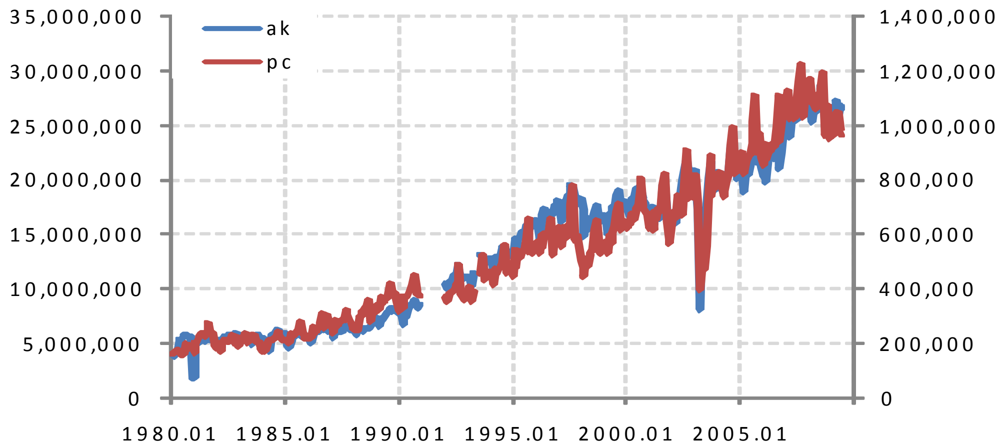
JAPAN AIRLINES | ICAO code: JAL
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

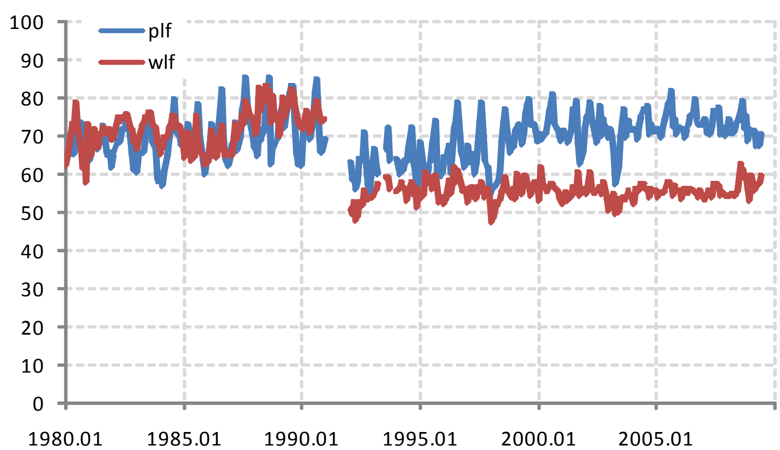




KOREAN AIR | ICAO code: KAL

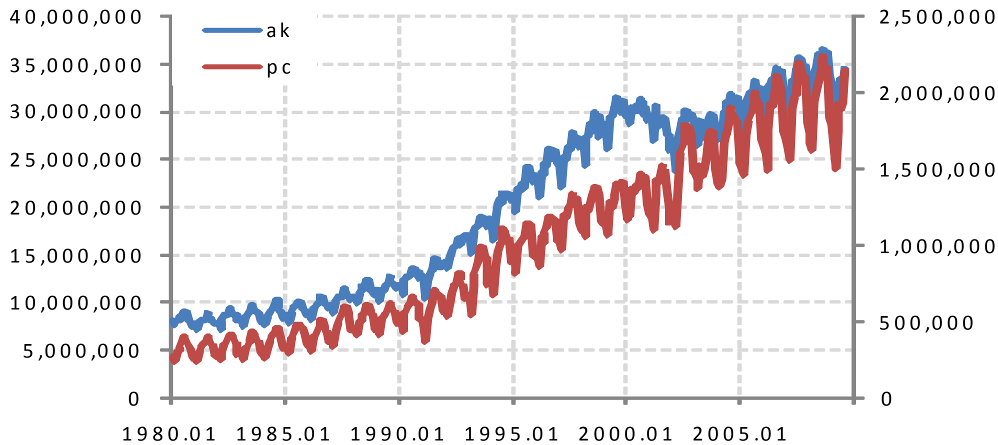
- Top panel: ak (LHS scale: kilometers flown in ‘000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

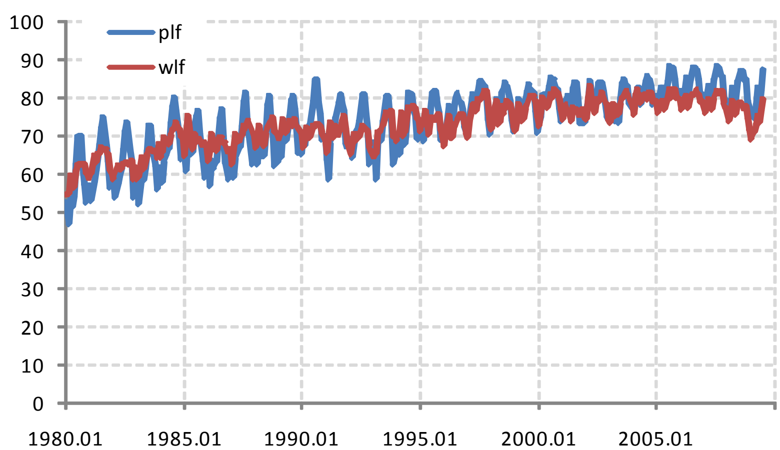




KLM | ICAO code: KLM

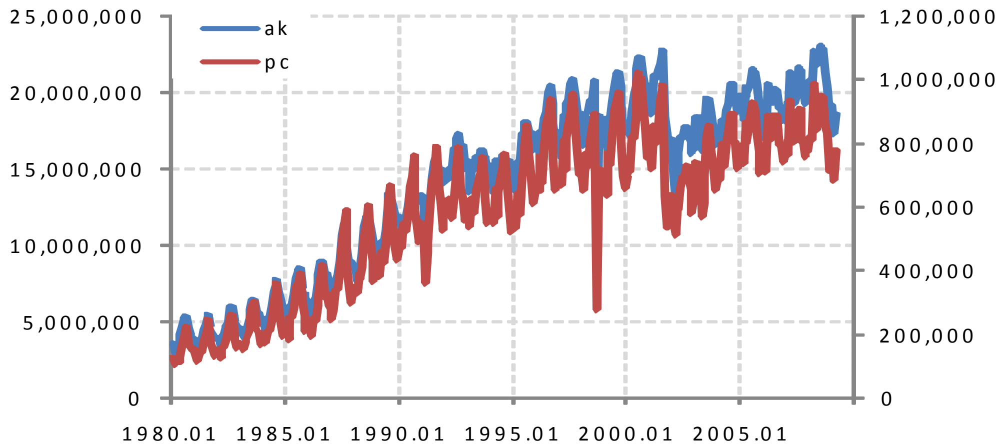
- Top panel: ak (LHS scale: kilometers flown in ‘000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

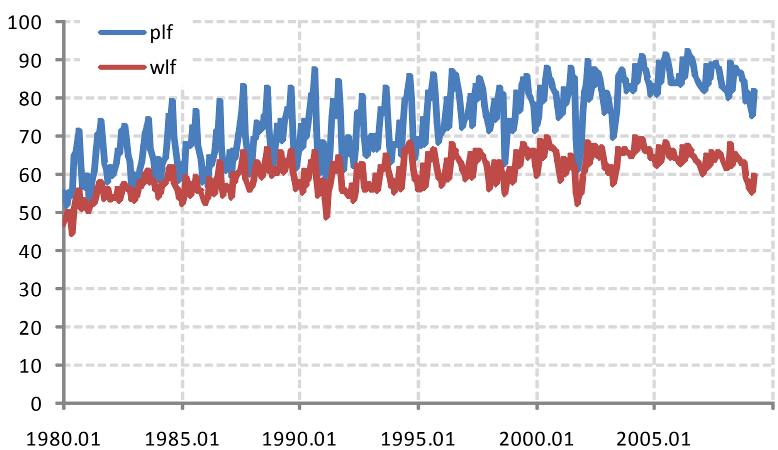




NORTHWEST AIRLINES | ICAO code: NWA

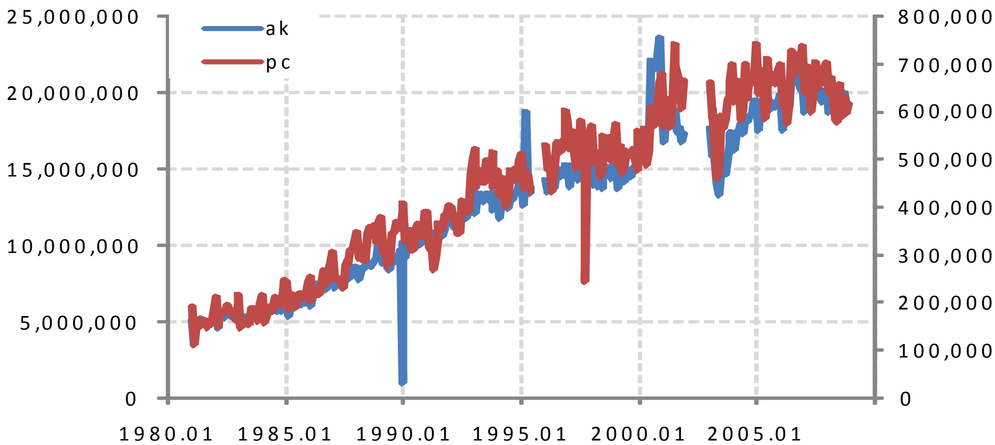
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

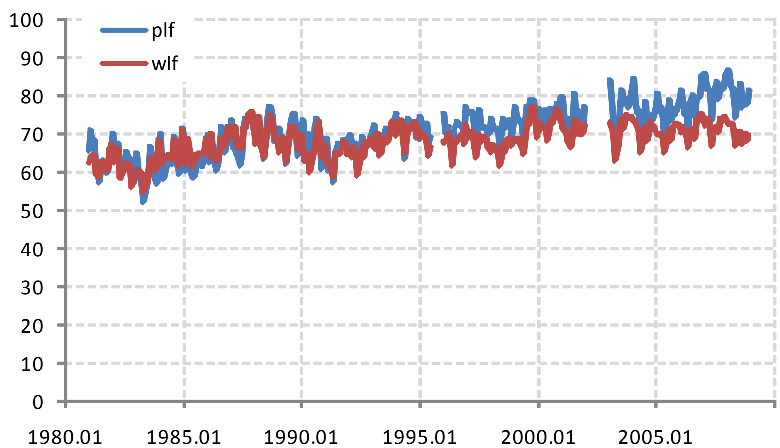




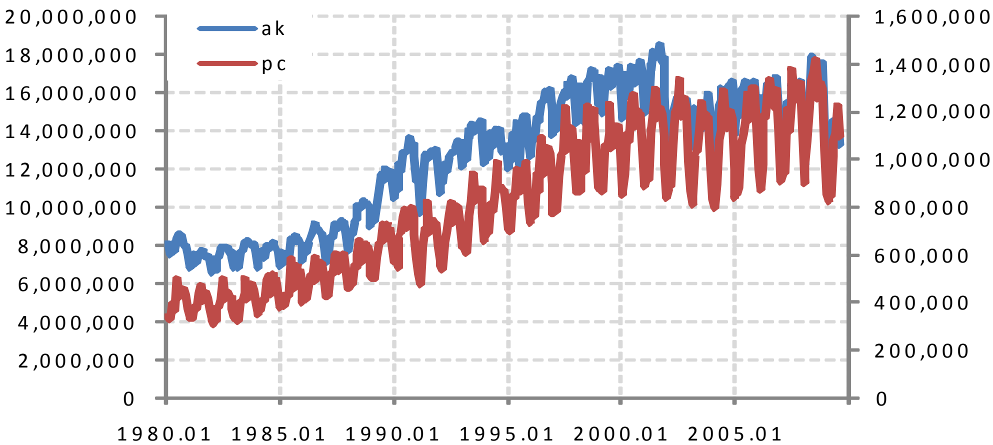
QANTAS | ICAO code: QFA

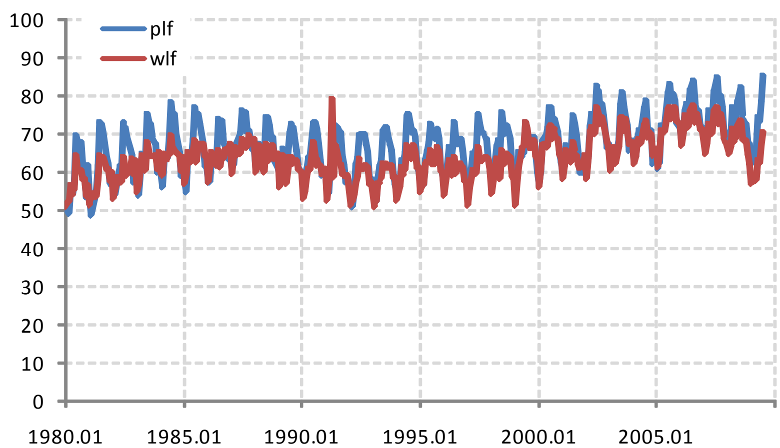
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009





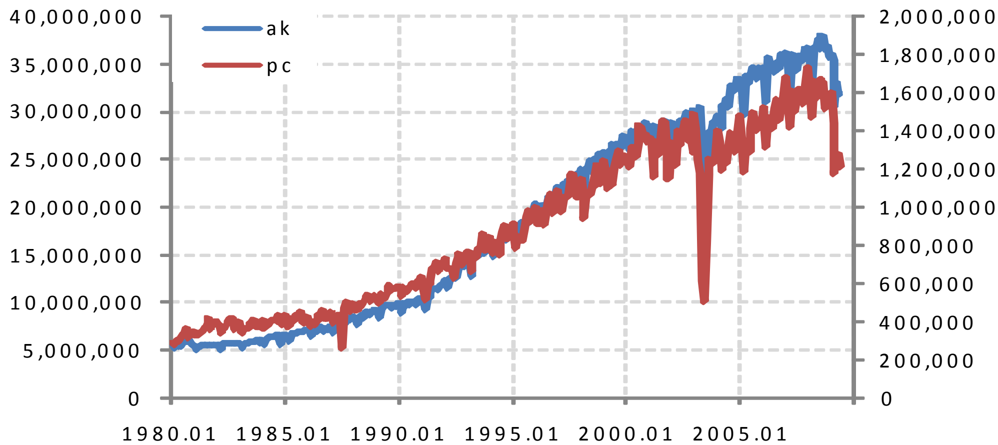
SCANDINAVIAN | ICAO code: SAS
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

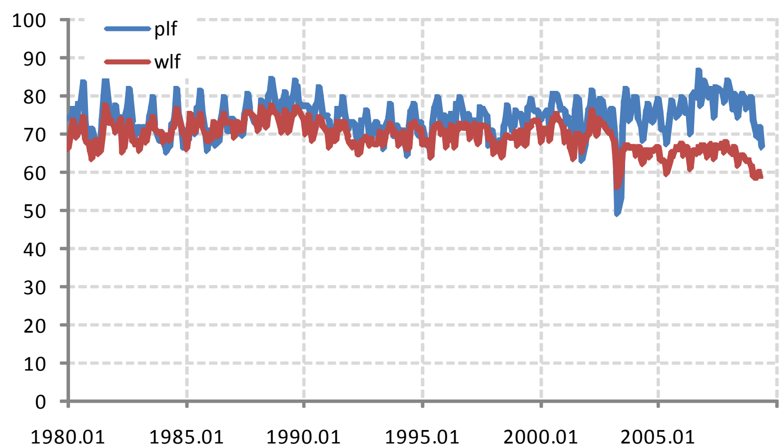




SINGAPORE AIRLINES | ICAO code: SIA

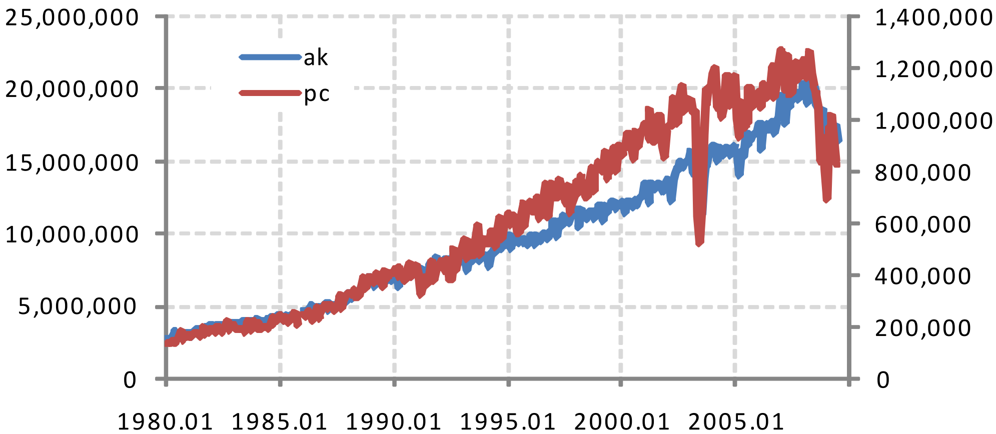
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

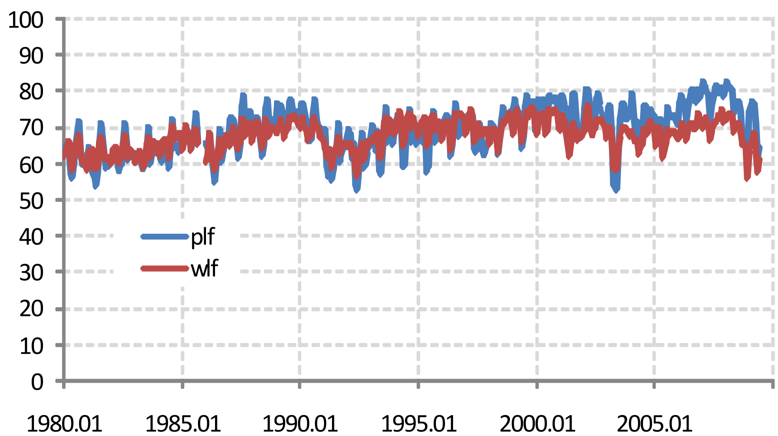




THAI AIRWAYS

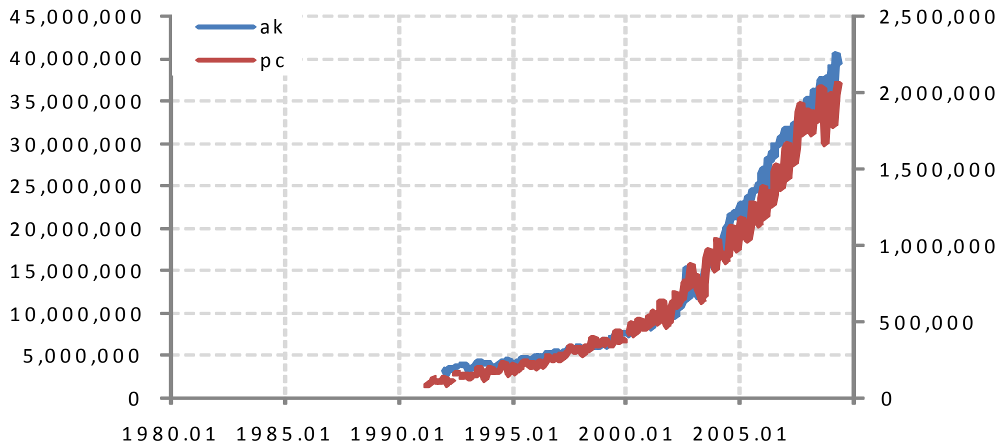
- Top panel: ak (LHS scale: kilometers flown in ‘000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

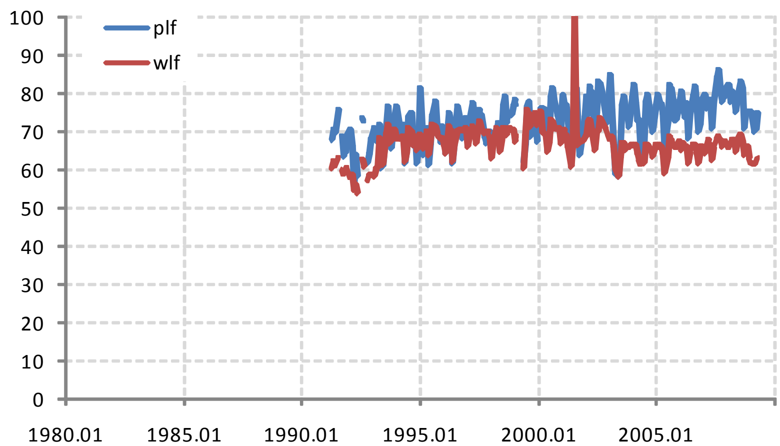




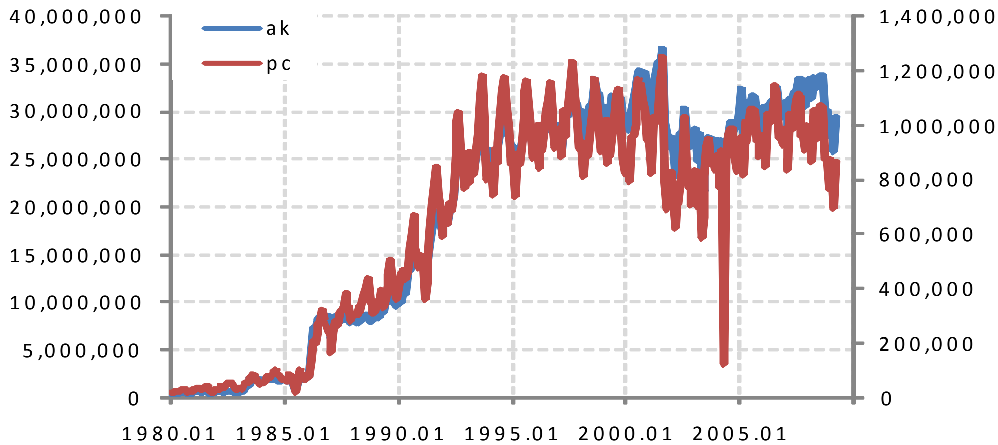
EMIRATES | ICAO code: UAE

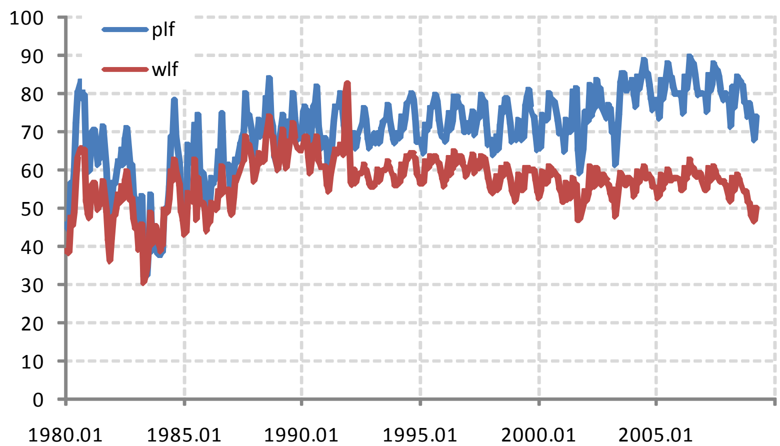
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009





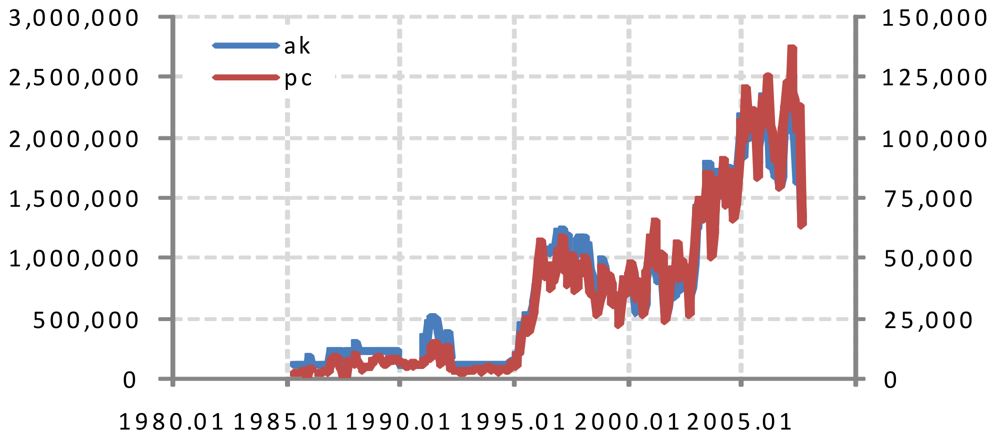
UNITED AIRLINES| ICAO code: UAL
- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009

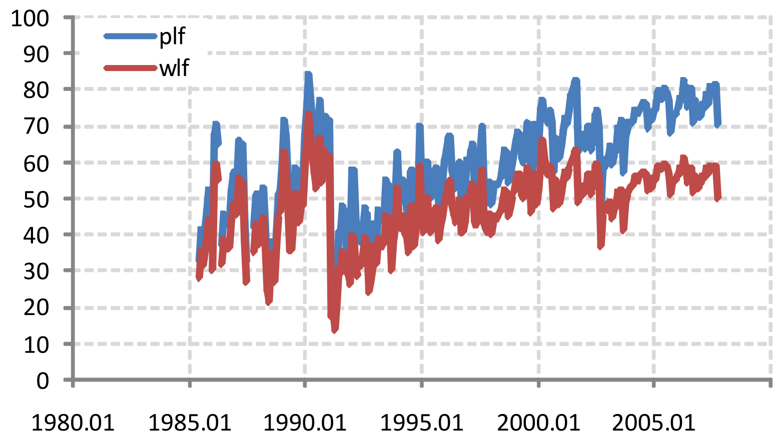




US AIRWAYS (formerly AMERICAN WEST) | ICAO code: AWA

- Top panel: ak (LHS scale: kilometers flown in '000s); pc (RHS scale: passengers carried)
- Bottom panel: plf, wlf (percent of available capacity)
- Horizontal axes: Jan. 1980 to Dec. 2009





Appendix C: Exploratory case studies (Air France, Delta Airlines, KLM, Lufthansa, United Airlines)

Given the degree of heterogeneity of results identified in the panel data estimates in the main text, particularly in the range of estimates for the mean group/random coefficients approach, it seemed worthwhile to investigate some individual airlines further. The panel methods restrict the same specification to be used across all airlines. Focusing on individual airlines allows the researcher more freedom of model specification. It also allows the use of different time-series methods that are not feasible for panels, potentially giving a better understanding of the time-series properties of the estimates. A number of researchers were given individual airline data, plus the general data and asked to provide an initial analysis. They not only provide a range of specifications, but also of estimation methods. On the whole, their findings are consistent with the main findings reported in the panel estimates, namely underpinning the argument that the degree of heterogeneity of experience of the individual airlines makes the results of aggregate analyses of seemingly little use in understanding the experience of individual airlines. Each airline is sufficiently unique from the others that little can be observed in the aggregate.

Air France

Eftychia Nikolaidou analyzed data for Air France using an Autoregressive Distributed Lag Model (ARDL) approach to cointegration. If present, this approach allows one to discover potential long-term statistical relationships among variables, i.e., apart from short-term (“one-off”) relations. ARDL does not require a priori testing for the integration properties of the variables. The empirical estimates presented here of this section are the outcome of extensive model specification searches following the “general to specific” approach.

Passengers carried (lpc): Looking at the short-run estimates of the ARDL model (Table A1), neither the total number of incidents (inc) nor the 9/11 dummy are statistically significant. Among the two unemployment variables, in the short-run only the U.S. unemployment is statistically significant, and with the expected negative sign. In the long-run, both the French and the U.S. unemployment are negative and statistically significant (Table A2). The Gulf war dummy seems to have had a significant negative effect on Air France demand when “passengers carried” is used as a proxy. This is also the only model specification where the Iraq war dummy (ddiraq) is statistically significant and negative, both in the short- and long-run (although only at the 10% level in the long-run).

Aircraft kilometers (lak): When the “aircraft kilometers” variable is used as a proxy for the demand for flights, both the Gulf war and the 9/11 dummy have negative and statistically significant effects. Also, a statistically significant negative effect exists from the French unemployment variable. In the long-run, the terror incidents (inc) variable is the only insignificant variable, meaning that there is no long-run impact of terrorist events on the demand for flights. In the ECM estimates, the change in the total number of incidents is

Table A1: Air France. Summary of ECM estimates

	lpc	*lak*	*wlf*	*plf*
dlinc	0.002	–0.004	0.009	–0.002
	(0.91)	(0.29)	(3.04)***	(1.41)
dlufr	–0.07	—	—	0.02
	(1.32)			(1.61)
dluus	–0.07	-0.04	—	–0.023
	(2.56)***	(2.10)**		(1.54)
ddgulf	-0.08	–0.04	–0.02	–0.04
	(3.52)***	(2.47)***	(1.85)*	(3.68)***
dd911	0.02	–0.03	0.012	0.008
	(1.27)	2.91)***	(2.61)***	(0.98)
ddiraq	–0.07	—	—	—
	(2.06)**			
dym	–0.004	0.006	—	0.001
	(1.93)*	(3.93)***		(2.31)***
dc	2.31	1.85	0.44	1.15
	(2.54)***	(3.98)***	(3.94)***	(3.30)***
ECM(–1)	–0.15	–0.11	–0.12	–0.28
	(2.51)***	(3.88)***	(4.25)***	(3.48)***
R2	0.73	0.69	0.85	0.94
DW	2.04	1.97	2.00	1.99

Note: *, **, *** denote statistical significance at the 10, 5 and 1% levels, respectively.

Table A2: Air France. Summary of long-run estimates

	lpc	*lak*	*wlf*	*plf*
linc	0.015	–0.004	0.077	–0.006
	(0.90)	(0.29)	(3.05)***	(1.53)
lufr	–0.44	—	—	0.09
	(1.95)**			(1.53)
luus	–0.48	–0.35	—	–0.08
	(2.24)***	(1.94)**		(1.83)*
dgulf	–0.51	–0.33	–0.17	–0.13
	(2.21)***	(2.17)***	(1.74)*	(2.56)***
d911	0.14	–0.29	0.10	0.03
	(1.21)	(2.51)***	(2.94)***	(1.00)
diraq	–0.47	—	—	—
	(1.66)*			
ym	0.003	0.006	—	0.001
	(4.43)***	(9.82)***		(3.33)***
c	15.29	16.89	3.72	4.11
	(27.28)***	(45.26)***	(26.18)***	(27.14)***

Note: *, **, *** denote statistical significance at the 10, 5 and 1% levels, respectively.

again the only insignificant variable.

Weight load factor (wlf): When the model is estimated with the "weight load factor" proxy, both the short- and long-run impact of the total number of incidents variable has a significant positive effect on the demand for flying by Air France. This is in contrast to initial expectations and implies that when there is an increase in the number of terrorist events the demand for Air France flights increases. The same unexpected finding applies to the 9/11 dummy (in the long-run significant only at the 10%), while among the terror and war incidents, it seems that only the Gulf war had a significant negative effect. The unemployment variables were insignificant and excluded from the model. As there was heteroskedasticity, we present White's adjusted standard errors.

Passenger load factor (plf): When the "passenger load factor" variable is used as a proxy for the demand for flights, the total incidences variable and the dummy for 9/11 are insignificant both in the short- and in the long run. Again, given the presence of heteroskedasticity, we present White's adjusted standard errors.

General: In most of the cases, an interesting result—and in contrast to our initial expectations—is that the total number of incidents (inc) variable has had no significant impact on the demand for flights by Air France. The only exception is when the "weight load factor" (wlf) is used as a proxy for the demand variable, in which case the inc variable is statistically significant with a positive sign. This implies that an increase in the number of incidents, increases the demand for flying by Air France. A possible explanation for this is that people stop using U.S. American airlines in particular and shift toward "safer" ones (Air France in this case) regarding terrorist attacks. Further, the impact of the 9/11 terrorist attack is statistically insignificant in two out of the four specifications (when the "passengers carried" and "passenger load factor" proxies are used for the demand for flights variable) while the variable is significantly negative under the "aircraft kilometers" specification but this changes to a significantly positive effect under the "weight load factor" specification. These diverse results regarding the impact of the 9/11-variable are difficult to explain.

In contrast, the dummy for the Gulf war appears to have a significant negative impact in all four specifications. This is not the case for the Iraq war dummy, which appears negative and significant only under the "passengers carried" specification of the demand variable. Finally, the unemployment variables appear negative and significant in most cases (the only exception is when the "weight load factor" is used as the dependent variable).

Conclusion: These results suggest that the demand for flights by Air France has not been much affected by the 9/11-attack or the total number of terror events worldwide. Regarding the number of terror events variable (inc), it appears insignificant both in the short- and in the long-run when aircraft kilometers, the passengers carried, and the passenger load factor variables are used as the dependent variable but positive and highly significant when the weight load factor variable is used. The only explanation we see for the positive effect of the last variable is that people switched to Air France after terror events as they may have considered Air France "safe" to fly in comparison to U.S. American or U.K. airlines, but then one would have expected the pc variable to carry a positive coefficient also. It would be of interest to compare the findings to those for airlines of countries, especially for U.S. and U.K., which seem more prone to suffer terror attacks. The fact that the Iraq war overlaps with the SARS dummy (which was also insignificant using all proxies) forced us to re-estimate the model excluding SARS. When we did that, the Iraq war dummy became negative and highly significant only under the "passengers kilometers" specification.

KLM and Lufthansa

Giorgio d'Agostino and Luca Pieroni provide a comparative analysis of Lufthansa and KLM airlines. Their findings further illustrate heterogeneity across airlines. They do find a strong link between terrorist attacks and the demand function in both the short- and long-run. Looking at aircraft kilometers and the number of passengers carried, it appears that KLM is more exposed to specific terrorist events and international conflicts, such as the 9/11-attacks or the Iraq war, than is Lufthansa. There seemed to be no cointegrating relation for the other indicators.

For Lufthansa, lag selection criteria suggested a cointegration test using 3 lags in each endogenous variable, and the procedure suggested one cointegration vector for the log of aircraft kilometers, the log number of incidents due to terrorist attacks, the log of passengers carried, and the log number of incidents due to terrorist attacks. The long-run results show a negative link between aircraft kilometers and the number of incidents due to terrorist attacks when only a 1998 shift-intercept is included in the model. As a first observation, they highlight a significant relationship between Lufthansa flight demand and the number of incidents due to terrorist attacks but there is no long-run evidence about any relationship between aircraft kilometers flown and specific terrorist events.

The results give support to their model, highlighting that both the lagged differences of the parameters of aircraft kilometers and the number of incidents due to terrorist attacks are of the expected sign and statistically significant, such that these proxies are able to explain the dynamics of the airline demand function also in the short-run.

For KLM, the lag selection criteria suggested the use of 4 lags in the analysis. They find one cointegration relationship. In this case, there is no long-run negative relation between aircraft kilometers and the number of incidents due to terrorist attacks for KLM, and the inclusion of the dummies does not increase the statistical significance of the parameters. The main result of a possibly questionable negative link between the KLM demand function and the number of incidents from terrorist attacks is not confirmed when we replicate the analysis using the number passengers instead of aircraft kilometers as the dependent variable. In this case, the parameter associated with the number of incidents from terrorist attacks is statistically significant. As for the Lufthansa estimates, the dimension of the parameter is high, suggesting that terrorist attacks strongly affect KLM's demand. In addition, and in contrast with the Lufthansa findings, the 9/11-dummy variable is statistically significant, which suggests that KLM's demand function is more exposed to U.S.-related events than is Lufthansa.

In the general estimates across airlines, terrorist incidents do not seem to influence kilometers flown, but this result is contradicted when passengers carried is used as the dependent variable. In this case, incidents do affect airline demand in the short-run, separate from significant seasonal fluctuations in Lufthansa's demand function.

Overall, the Johansen cointegration procedure confirms a long-run relationship between terrorist attacks and airline demand. First, the use of passengers carried by each airline company does seem to be a proxy for the demand function of the company. Second, KLM seems to be more exposed to specific terrorist or international conflict events. Third, although the impact in the short-run is less strong than with respect to the long-run, the estimated parameters are statistically significant. In conclusion, the initial analysis suggests that both airlines, KLM and Lufthansa, could have seen significantly increased demand if worldwide insecurity due to terrorist attacks had been lower than it in fact was. KLM, being more exposed, would have seen the bigger increase in demand.

Delta Airlines

Ali Tasiran provided a brief case study of Delta Airlines, finding that statistical tests indicate nonstationary of kilometers flown and passenger carried per month, and stationary of passenger load factor and weight load factor in percent of available seat/weight capacity. Test results suggest that apart from plf, the series are cointegrated. Estimating an Error Correction Model (ECM) for the four dependent variables (ak, pc, plf, wlf) for the different measures of terror events (incidents, killed, wounded, and casualties), his work finds that the only statistically significant coefficient estimates of an adverse effect of large-scale violence on Delta Airlines stems from the Iraq war, and here only in the models using incidents and numbers killed. In particular, this suggests that the general level of terrorist incidents has not affected Delta Airlines.

United Airlines

Nadir Öcal undertook a study of United Airlines using a Vector Autoregression (VAR) and Vector Error Correction (VEC) analysis. Unit-root tests result mostly in implied nonstationarity, and all variables are assumed integrated of order 1. The first differences of all variables were found to be stationary.

For passengers carried, the information criteria for the lag selection suggested a 12-lag model and cointegration analysis results indicate that there is one cointegrating vector among passenger carried, total terror incidents, and the U.S. unemployment rate which was estimated as $lpc_t = -0.082(linc_t) -20.455(luus_t)$. This relationship between the variables is as expected: As the number of terror incidents or the U.S. unemployment rate increase, passengers carried decrease. For reasons of parsimony, insignificant variables were dropped from the model and the model estimated again by FIML. But the first model performs better in terms of the size and significance of the error correction term.

For the weight load factor variable, the criteria for lag selection suggested a lag-length of 3 and tests for cointegration suggested one cointegrating vector among weight load factor, terror incidents, and the U.S. unemployment rate, the cointegrating vector being $wlft = -0.165\ (linc_t) -0.142(luus_t)$. Again, the relationships are as expected: As the number of terror incidents or the U.S. unemployment rate rise, the weight load factor decreases. Again, this is re-estimated with FIML after dropping the insignificant variables. Overall, the results provide some evidence that the number of terror incidents affects the passengers carried variable, but the effect is small relative to economic effects as proxied by U.S. unemployment. The effect of the number of terror incidents on the weight load factor variable seems stronger than U.S. unemployment in the long-run, but there seems to exist no short-run effect.

In sum

As repeatedly emphasized, these are exploratory case studies. While in no way conclusive, they certainly did not result in anything close to a uniform outcome. To the contrary, even these initial results point to the need to model air traffic demand for each airline in highly tailored, airline-specific ways. This would confirm one of the primary results referred to in the main narrative of this Report: Airline demand is heterogeneous, and the same external event, such as a particular war or terror event, affects diverse airlines in diverse ways. Given our statistical work, it may be disingenuous for the airline industry, or other commentators, to bespeak the impact of particular large-scale violent events for the industry as a whole.