7-29-2021

Aviation Economics: Safety, Monopsony, and Small Sample Inference

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ABSTRACT

AVIATION ECONOMICS: SAFETY, MONOPSONY, AND SMALL SAMPLE INFERENCE

BY

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December, 2021

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This dissertation consists of three essays on aviation. The first chapter investigates the relationship between competition and airline safety. The U.S. airline industry transports almost a billion passengers a year. Accidents still cause much apprehension and angst among the public; the two 737 Max crashes are the latest examples. Despite massive improvements in safety over the last decades which are largely due to technological improvements, there is still a lack of research done on the effect of market conditions. We provide a simple theoretical model to explain the relationship between safety and competition. Using data from 1995 to 2018, we employ a negative binomial regression to evaluate the impact of competition through the Inverse Herfindahl Hirschman Index, Concentration Ratio 4 and 8, on injury outcome of passengers involved in an airline accident. Since accidents are costly both directly and indirectly through brand image deterioration, a competitive market may incentive airlines to reduce risks of accidents. Meanwhile, since safety is unobserved by passengers, under a highly competitive environment where profit margins are thinner, airlines cut costs, some of which are related to safety. Our result suggests that a less competitive industry has a positive impact on safety, suggesting that excess profits are in part reinvested into safety measures.

The second chapter tests the hypothesis that monopsony power is an important determinant of wages and employment in the U.S. pilot labor market. We estimate the labor supply curve of the U.S. airline industry using firm-level employment and accident data from 1995 to 2018. Utilizing a labor demand instrument, the prevalence of aircraft accidents, allows us to directly measure monopsony power. We also investigate the effects of competition, as measured by the Inverse

Herfindahl-Hirschman Index, on the labor supply elasticity. We estimate a labor supply elasticity of 2.56, indicating that airlines have substantial monopsony power in pilot hiring, resulting in a labor shortage and wages 28.11% below the marginal revenue products. We also find that as market competition rises, airlines slightly lose market power in hiring: wages increase as competition increases. The source of monopsony power lies elsewhere, mostly in the training and career structure, which we address and provide policy recommendations.

The third chapter proposes a new method to calculate the p-values of a treatment variable in a cross-sectional small sample. Causal evaluation is becoming increasingly popular in industry and government. In small sample scenarios inference is more difficult. This often occur for several reasons such as budget constraints or noncompliance, but also in phenomena with low frequency. Small samples complicate causal evaluations for at least three reasons: (i) they are associated with greater sampling error, (ii) p-values based on standard tests are not trustworthy and the statistical power of these tests can be too low to detect significant program effects, (iii) the validity of parameter inference strongly depends on distributional assumptions. This paper proposes a simple approximation for the p-values to use in the regression analysis of treatment effects models with normal or nonnormal error distributions. The approximation is derived from recent developments in likelihood analysis and has a third-order distributional accuracy. Thus, for very small or medium-sized samples, the proposed method has a remarkably higher accuracy compared to traditional ones that usually rely on normality or large samples. The method is then applied to aviation data to evaluate the impact of accidents on airfares, which is relevant to both airlines and insurance companies.

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By

Marc Sleiman

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY

2021

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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December, 2021

ACKNOWLEDGMENTS

This dissertation has only been possible because of the encouragement and endless support of my advisors, mentors, colleagues, friends, and family.

First, I would like to start by thanking my family who have provided endless support. Thank you, mom, dad and brother, for your unconditional love and understanding. This would not have been possible without you.

Next, I would like to thank my advisor, Dr. Pierre Nguimkeu, The Parangon, for his guidance through the entire doctoral process. It has been a privilege to work so closely with such a multitalented academic. Dr. Nguimkeu has always supported, advised, and mentored me through a multitude of professional situations. I will always be in grateful for the time he has spent working with me. I am very grateful to Augustine Denteh for his guidance, suggestions, and encouragement. Through his kindness and generosity, he helped me navigate through many hurdles. I thank Dr. Feltenstein and Melkadze for their valuable feedback and benevolence.

I would also like to thank Madame Lefevre, Monsieur Guessant, and Monsieur Boichu for igniting in me my mathematical abilities that have been essential for this journey. Many thanks to my friends Deo Mujwara and Yasin Civelek for accompanying me into our common journey since our first day at Georgia State University, as well as Ernest Dorillas and Bela Figge in my cohort for their cooperation and constructive exchanges.

I would also like to thank my friends, Alireza Lavassani, Marwan Chawqi, and Frank Achoundong, for their continual support. Lastly, I would like to give a special thanks to Hamid Lavassani for providing me perpetual mentorship and support.

It is because you all have provided such kindness, support, and encouragement that I have accomplished my journey.

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Introduction

This dissertation consists of three essays on aviation. The first chapter investigates the relationship between competition and airline safety. The U.S. airline industry transports almost a billion passengers a year. Accidents still cause much apprehension and angst among the public; the two 737 Max crashes are the latest examples. Despite massive improvements in safety over the last decades which are largely due to technological improvements, there is still a lack of research done on the effect of market conditions. I provide a simple theoretical model, adapted from (Golbe, 1986), to explain the relationship between safety and competition. Using data from 1995 to 2018, I employ a negative binomial regression to evaluate the impact of competition through the Inverse Herfindahl Hirschman Index, Concentration Ratio 4 and 8, on injury outcome of passengers involved in an airline accident. Since accidents are costly both directly and indirectly through brand image deterioration, a competitive market may incentive airlines to reduce risks of accidents. Meanwhile, since safety is unobserved by passengers, under a highly competitive environment where profit margins are thinner, airlines cut costs, some of which are related to safety. My result suggests that a less competitive industry has a positive impact on safety, suggesting that excess profits are in part reinvested into safety measures. I find that older pilots are safer. Since there is a pilot shortage, airlines and the Federal Aviation Administration (FAA)are looking into ways to find and retain pilots. In light of the ongoing discussion to extend the retirement age from 65 to 67, this chapter is in favor of extending the retirement age. Also, since a less competitive market provides safety, I propose that the FAA creates new Safety Performance Index's (SPI), one that takes into account accident severity (and not just frequency) and one that is ex-ante by performing more audits. The latter will increase barriers to entry, which should help the market be less competitive while encouraging safety.

The second chapter tests the hypothesis that monopsony power is an important determinant of wages and employment in the U.S. pilot labor market. I estimate the labor supply curve of the U.S. airline industry using firm-level employment and accident data from 1995 to 2018. Utilizing a labor demand instrument, the prevalence of aircraft accidents, allows us to directly measure monopsony power. We also investigate the effects of competition, as measured by the Inverse Herfindahl-Hirschman Index, on the labor supply elasticity. We estimate a labor supply elasticity of 2.56, indicating that airlines have substantial monopsony power in pilot hiring, resulting in a labor shortage and wages 28.11% below the marginal revenue products. We also find that as market competition rises, airlines slightly lose market power in hiring: wages increase as competition increases. The source of monopsony power lies elsewhere, mostly in the training and career structure. Specifically, the U.S. has a unique training and hiring mechanism that delays a pilots entry into a major airline. Pilot training takes at least 4 years, with a large requirement on flight hours to be able to join a regional airline for a few years to be eligible to join a major airline. In most of the world, pilots are quickly trained to access any airlines. I propose that the U.S. goes through a similar system, by including ab initio training. As a pilot's compensation is highly dependent on seniority, a sooner entry into a major airline will increase lifelong earnings.

The third chapter provides a new method for approximating the p-value for a treatment variable in small cross-sectional samples. Causal evaluation is becoming increasingly popular in industry and government. In small sample scenarios inference is more difficult. This often occur for several reasons such as budget constraints or noncompliance, but also in phenomena with low frequency. Small samples complicate causal evaluations for at least three reasons: (i) they are associated with greater sampling error, (ii) p-values based on standard tests are not trustworthy and the statistical power of these tests can be too low to detect significant program effects, (iii) the validity of parameter inference strongly depends on distributional assumptions. This paper proposes a simple approximation for the p-values to use in the regression analysis of treatment effects models with normal or nonnormal error distributions. The approximation is derived from recent developments in likelihood analysis and has a third-order distributional accuracy. Thus, for very small or medium-sized samples, the proposed method has a remarkably higher accuracy compared to traditional ones that usually rely on normality or large samples. The method is then applied to aviation data to evaluate the impact of accidents on airfares, which is relevant to both airlines and insurance companies. Results show that the confidence interval found in our third-order likelihood method differs from other first-order likelihood methods, which affects inference.

Chapter 1

Competition and Airline Safety

1.1 Introduction

The aviation industry, which represents approximately 5.2 percent of Gross Domestic Product and 376,000 jobs in the United States, faces substantial obstacles, such as volatile oil prices Hansman et al. (n.d.), and a pilot shortage (Meredith, 2018). Worldwide, air traffic grows at a high rate, doubling every fifteen years (Airbus, 2017). In the United States, there is nearly a billion passengers traveling a year [1]. Safety is a major concern for travelers and has significantly improved over the past decades, so much that it has become the safest mode of transportation. Specifically, over the past two decades, there has been a reduction in American commercial aviation fatalities by 95 percent FAA (2018); worldwide accidents have fallen by 80 percent since 1997 (Airbus, 2017). The International Civil Aviation Organization (ICAO), a branch of the United Nations, adopts and recommends practices that all member countries should follow. An example is the use of Safety Performance Indexes (SPI) to keep track of the safety record in the respective country. An SPI is defined by the ICAO as the process of measuring and monitoring safety related outcomes associated with a given operational system or organization (Thong, 2015). Such safety improvements are also due to advances in technologies, infrastructure, and labor training, as well as oversight by the Federal Aviation Agency (FAA, 2018). Meanwhile, it should be mentioned from the start that aviation safety is not a definite term, as it can vary in both frequency and severity. Frequency is measured as accident rate, while severity can be measured both in terms of aircraft damage and passenger injury (Moses and Savage, 1990). Aviation accidents are expressed by accident rates (eg, per million departures), which allows for more relevant comparison. As stated by Phillips and Talley (1996), analyzing the evolution over time remains problematic because accidents vary in severity. Some accidents can be minor, with a single person slightly injured (for example by turbulence). Others can be major, where death is the unfortunate fate of everyone on board (Moses

[1] https://www.bts.dot.gov/newsroom/2018-traffic-data-us-airlines-and-foreign-airlines-us-flights

and Savage, 1990). Most research regarding airline safety was conducted in the 1990?s to examine the effect of the Airline Deregulation Act that deregulated the airline industry in 1978. While this abrupt shock has changed the competitive environment and was worth investigating, little work has been done to examine how changes in competition would affect safety from a more general perspective. Accidents cannot be entirely prevented, and the last two fatal crashes related to the Boeing 737 Max (grounded as of this writing) have, for some, awakened fear of travel and shown us the importance of safety in the airline industry. Aircraft safety is one of the most important characteristic an airline can aim to achieve. While it is of tremendous importance, it is also unobserved by passengers. Hence there runs the risk of airlines underproviding safety, whether intentional or not, especially when there is stress on profits. While under-regulation can leave too much leeway for airlines to take a risk by cutting back on safety, too much regulation may also have detrimental effects due to the large compliance costs. Multiple studies have shown that consumers are willing to pay for a safer product (Saad, 2007; Ortega, Wang, and Olynk Widmar, 2015). Such a difference in consumer's willingness to pay for safety is founded on the fact that the consequences can be dire otherwise. Partial liability and reputation concerns motivate firms to make socially desirable safety investments. Furthermore, the fear of flying adds to the distortion of passenger's risk assessment. This fear is irrational, and this can be demonstrated with different statistics. For instance, the mortality rates for air travel and automobile travel is 0.07 and 7.28 fatalities per billion passenger miles respectively; air travel is over a hundred times safer (Weisman and Van Doren, 2020). Additionally, Chen and Hua, 2017 explain how the greater the reputation loss, the greater the safety investments. With all the media hype concerning aircraft accidents, reputation is a strong motivator to not cut on safety too much. Airlines also face product liability, thus if they operate a low-safety operation, they face both high liability and high reputation loss. However, despite these three factors incentivizing airlines to produce some safety, there is an inherent risk that they would underprovide it since it is unobserved. Generally, economists believe that competitive markets are better for consumers than consolidated markets. While this holds true for prices, it may not be the case for safety, as it is not for customer satisfaction in the airline industry. The purpose of this research is to further examine whether or not this finding holds in the U.S. commercial airline industry for the dimension of safety by examining the effect of competition on passenger injury severity. We find that as the market becomes more competitive, passenger injuries get worse, meaning that a competitive environment can have negative consequences on safety.

1.2 Literature Review

1.2.1 The Impact of Accidents

Commercial aircraft accidents are costly, both directly and indirectly. Direct costs include costs of repairs, passenger and family compensations, underutilization of capital, and the loss of lives and injuries. Meanwhile, indirect costs include brand image deterioration, loss of economic efficiency of injured passengers, and loss from insurance companies (CMTA, 2015). (Čokorilo et al., 2010) made a study on evaluating the costs of an aviation accident by taking the case study of an Airbus A320, which is a medium haul aircraft, carrying around 150 passengers. The authors classify the costs of the aircrafts "physical damage, loss of resale value, loss of use, site contamination clearance, airline costs for delays, airport closure, deaths and injuries, loss of staff investments, loss of baggage, search and rescue costs, airline immediate response, cost of investigation, third party damage, increased cost of insurance, loss of reputation, and other costs." Some assumptions were made in the cost evaluation, such as a 6 month period to repair an aircraft, airport closure is omitted, investigation costs are half a million €, third party damage is omitted, the value of statistical life (which is how much society is willing to pay to prevent a fatality) is 1.82 million €, the minimum and maximum cost of loss of reputation are 0 and 380 million €, respectively. As plane depreciates, the formula uses the aircraft age in years to compute the cost bounds. Results show that the minimum and maximum costs for a 12-year-old A320 with minor damage to be 34 million €, and 414 million €, respectively. The minimum and maximum costs for an A320 that has 0 years of age, and catastrophic damage are 211 million €, and 591 million €, respectively. Surviving passengers also suffer from Post-traumatic Stress Syndrome (PTSD) regardless of their level of injury (Gouweloos et al., 2016).

In terms of financial cost, several studies have examined the effect of a crash. Research by (Li et al., 2015) examined the impact of TransAsia Airways GE222 accident on July 23rd, 2014 in Taiwan on public perception. The authors studied the relationship between the stock price fluctuation and the media index.[2] Interestingly, during the survey, there was another accident on flight GE235 that occurred. In the wake of the accident, public perception was initially negative, but improved over time as the accident fades away from memory. Results also showed that survey respondents that participated both before and after the last accident were significantly more affected. Meanwhile, over time, public perception improves, and confidence towards the affected airline is gradually regained but will regress again with an accident recurrence. Lastly, the authors find that the media have a significant influence on public perception, and can accentuate the fear of flying, which impacts the stock price Li et al. (2015).

Any negative media coverage on an aircraft accident affects public perception, and thus demand for air travel. (Zotova, 2017a) has examined the effect of a crash on airline pricing using the case of Alaska Airline Flight 261.[3] By looking into the effects of the crash on airfares[4], the author has found that the relative fares of Alaska Airlines compared to its competitors have dropped for a few months after the crash, accompanied with a decrease in the number of passengers. The latter is coherent with the findings of (Bosch, Eckard, and Singal, 1998), that has shown that airline stocks react to demand shocks of accidents to reflect the airline's impact on revenue. Hence, clearly a severe accident such as a crash causes a reduction in travel demand.

1.2.2 Deregulation

Concern for air safety had attracted attention from economists, particularly after the Airline Deregulation Act of 1978 was signed by the then-President Jimmy Carter. Experts were afraid that the deregulation, which increased the number of players in the industry, had put pressure on profits. A

[2]The media index was computed by taking the expected value based on news readership of the sum of the number of news article posted on different news sources.

[3]The flight from Puerto Vallarta, Mexico to Seattle, Washington state had crashed into the ocean. Unfortunately, there were no survivors.

[4]a difference in difference model was employed on airfare data obtained from the DB1B database.

higher level of competition may incentivize airlines to cut back on expenses such as maintenance, which may affect air safety. Talley and Bossert Jr (1990) have conducted a study examining the determinants of aircraft accidents[5] and found that relative maintenance expenditures were cut, but were not statistically significant in predicting accidents, while pilot experience was. This research has been confirmed by Kennet (1993) who examined data obtained by engine manufacturer Pratt & Whitney. After the deregulation, airlines had put more hours of use on their aircraft engines before their next overhaul, but this did not cause a rise in engine failures. Hence, the stronger forces from the competitive market had incentivized airlines to adapt by improving maintenance quality. Meanwhile, these results are not sufficient to claim that the competitive forces of the markets do not affect safety.

Phillips and Talley (1992) investigated factors that determined air safety from a perspective of aircraft damage.[6] Results of the study showed that pilot experience and airline safety investments significantly reduced the severity of aircraft damage during an accident. By employing the same data, Phillips and Talley (1996) looked into determinants of airline accident severity from a passenger perspective[7] and also found that pilot experience was a significant determinant in improving safety. Both pieces of research had found that commuter airlines were less safe than scheduled carriers.

Meanwhile, the studies did not look into the effects of the pilot's age on safety[8] Since the retirement age of commercial pilots has shifted from 60 to 65 in December 2007, it is particularly relevant today (Bahrami, 2009).

Safety is difficult to observe by consumers, and its equilibrium level is difficult to determine. Hence it is unknown whether or not consumers accurately estimate the probability of accidents and

[5]Talley and Bossert Jr (1990) employed linear and log-linear model on data from the National Transportation Safety Board (NTSB), the FAA Statistical Handbook of Aviation, and the FAA's Public Affairs Office in Washington.

[6]The authors employed data from the NTSB from the years of 1983 to 1986. Since aircraft damage severity is a categorical dependent variable, an ordered probit model was used.

[7]The SUR model was used to look at the different levels of injuries.

[8]age has a 55% correlation with flight experience (measured in total flight hours) for pilots are scheduled carriers. Pilots take different tracks to building hours to be eligible to enter a company that offers a stable job. For instance, the Air Force track is a 10 year contract, where pilots fly less 20 (Pawlyk, 2018) hours a month in comparison to airline pilots who fly at least 65 (we had access to a Delta Airlines contract to obtain this information).

incidents, which are, nevertheless, rare. Moses and Savage (1990) explain that safety is a function of three categories. First, economic incentives, which are insufficient since airlines have an incentive to under provide safety since it is hard for passengers to determine. Hence, comes the second category, surveillance. It is usually done by the government, but not always efficient. Lastly, since passengers, airlines, and the government employ airports and use airspace, the third category, infrastructure, is a crucial component to safety. By examining multiple research, the authors do find that despite an improvement in safety after the implementation of the Airline Deregulation Act, there was a lack of infrastructure investment and surveillance that could be responsible for some of the accidents.

1.2.3 Competition and Quality

Generally, economists believe that competitive markets are better for consumers than consolidated markets. While this may be true in most dimensions observed by consumers, it may not always be true. For instance, recent studies reveal that mergers can have positive outcomes for consumers as well. A study on the merger between United and Continental Airlines shows an increase in customer satisfaction(Andersen and Weisstein, 2019). A study on the consolidation of the freight railroad industry finds that "market consolidation appears to be an effective safety tool" (Shashoua, Sridhar, and Mittal, 2017). The authors urged managers to look at the effect of merger on not only revenue and sale but also substantial "indirect savings from safety improvement." The authors also pointed to the higher prices as a resource for improving safety.

For decades, the industry has witnessed many airlines emerge, merge, and shut down operations. Changes in the airline market concentration have led economists to mostly investigate airline mergers. (Kwoka and Shumilkina, 2010) has studied airfare fluctuations after the merger of USAir and Piedmont and found that if a route was served by one carrier, and the other was a potential entrant, then ticket prices on that route would increase by 5 to 6 percent. (Luo, 2014) has analyzed the effect of market competition and market price by instigating the merger between Northwest and Delta Airlines. Results have shown that airfares on routes that the two airlines competed on did not change significantly after the merger. Additionally, results showed that changes in the presence of low-cost carriers have a much larger effect on prices than legacy carriers. Meanwhile, (Shen, 2017) has examined the price effects of the United and Continental Airlines merger, which are two legacy carriers and found that routes on which the two used to compete with have seen an increase in airfare by 7.8 percent, but fares on adjacent routes have not changed much.

1.2.4 The Government's Role

Safety is difficult to observe by consumers, and its equilibrium level is difficult to determine. Hence it is unknown whether or not consumers accurately estimate the probability of accidents and incidents, which are, nevertheless, rare. Moses and Savage (1990) explain that safety is a function of three categories. First, economic incentives, which are insufficient since airlines have an incentive to under provide safety since it is hard for passengers to determine. Hence, comes the second category, surveillance. It is usually done by the government, but not always efficient. Lastly, since passengers, airlines, and the government employ airports and use airspace, the third category, infrastructure, is a crucial component to safety. By examining multiple research, the authors do find that despite an improvement in safety after the implementation of the Airline Deregulation Act, there was a lack of infrastructure investment and surveillance that could be responsible for some of the accidents.

A modern example of governance failure is in the case of the two Boeing 737 Max crashes, which were in some ways due to inadequate FAA oversight. The FAA had delegated too much responsibility to the manufacturer to certify parts of the new aircraft (Seattle-Times, 2019). The proper amount of delegation from the FAA to the manufacturers must be investigated, especially since we are about to see many changes in transportation.[9] Investments in infrastructure to improve safety and attain environmental sustainability have been part of the FAA's agenda. The FAA is in

[9] For one, artificial intelligence will eventually reduce the number of pilots in command from currently two to one (Bellini, 2018). Supersonic jets may see the sky again after the Concorde retired in 2003 (Gulliver, 2018). Lastly, the modernization of the air transportation system in an environmentally sustainable way is a primary national objective (FAA, 2015).

charge of implementing safer, more efficient, and environmentally responsible air transport through its Next Generation Air Transportation System. With a budget of $35.8 billion over about two decades, the total benefits are valued to be $160.6 billion by 2030 due to improvements in safety and efficiency (NexGen, 2016).

1.2.5 Technology Improvements

In addition to government regulatory work, technologies to improve aircraft safety have been drastic since the 1960s. The positive result also comes from a combination of developments in multiple areas. First, the engineering of aircraft and cockpit technology have significantly reduced accidents. Each new generation of aircraft has offered significant safety improvements[10]. For example, the inclusion of more automation, weather radars, Traffic Collision Avoidance System (TCAS), and a wind shear detection system have improved safety and significantly reduced the Loss of Contol (LOC) (Airbus, 2017)[11]. Second, infrastructure investments, that include ground radars to monitor aircraft at the airport and during low visibility, weather radars, and communication technologies have their role to play. Technology improvements have been enhanced by advances in communication protocols. The industry's ability to share learned lessons of accidents plays a sizable role. For instance, the aviation industry adopted a common practice called Crew Resource Management (CRM). CRM is a means of communication, cooperation, and behavior among all crew members, both onboard and on the ground. It is applied in situations where human error can have disastrous consequences. Captain Chesley Sullenberger's

[10]First generation of aircrafts are the early commercial jets from 1952 that have dials and guages in cockpit, and early auto-flight systems. Aircrafts include Comet, Caravelle, BAC-111, Trident, VC-10, 707, 720, DC-8, Convair 880/890. Second generation jets from 1964 have further integrated flight automation with elaborate auto-pilot and auto-throttle systems. Aircrafts include Concorde, A300B2/B4, Mercure, F-28, BAe146, VFW 614 727, 737-100 & -200, 747-100/200/300/SP, L-1011, DC-9, DC-10. Third generation aircrafts from 1980 have glass cockpit, electronic cockpit displays, improved navigation performance and Terrain Avoidance Systems, to reduce CFIT accidents. Aircrafts include A300-600, A310, Avro RJ, F-70, F-100, 328JET, 717, 737 Classic & NG, 757, 767, 747-400/-8, Bombardier CRJ, Embraer ERJ, MD-80, MD-90. Fourth generation aircrafts have fly-by-wire technology that helps protect flight envelope. Aircrafts include A318/A319/A320/A321, A330, A340, A350, A380 777, 787, Embraer E-Jets, Bombardier C-Series (Airbus, 2017)

[11]"Studying the statistics over the life of each generation of jets shows that an 85% reduction in fatal CFIT accidents has been achieved between the second and third generation of jets. In addition to this achievement, the fourth generation of jets has added a 75% reduction in fatal LOC-I accidents compared to the third generation."

astonishing landing in the Hudson River is in part due to such a training system (Shively et al., 2018). Moreover, data sharing among airlines, manufacturers, and authorities have also enabled them to identify risks that need to be addressed more effectively and improve safety research.[12].

During the 1990s, there was much academic research done in the area of aviation safety, particularly to study the effects of the Airline Deregulation Act of 1978. Since then, transportation economists have done less to examine safety in the aviation sector when it comes to understanding the impact of competition. This paper intends to pick up again the work on airline safety. Specifically, the contribution will reexamine the factors that affect injuries of those onboard, both fatal and non-fatal, and investigate how market competition affects human safety in the airline industry.

The rest of the paper proceeds as follows. Section 3 will provide model to illustrate the relationship between safety and competition. Section 4 will discuss the model, variables, and specification used to examine the factors that affect accident severity on passengers and crew members. Section 5 provides a discussion on the data and the results obtained from estimating our model. Section 6, the final section, provides a conclusion.

1.3 Model and Variables

1.3.1 A Simple Illustrative Model of Safety and Competition

The purpose of this section is to provide a simple illustration of how competition affects safety to provide intuition behind the ongoing mechanism. We adapt the model of (Golbe, 1986) by incorporating competition and changing the measure of safety (to a more abstract notion to incorporate severity rather than just having frequency) in her model of safety and profits. In this model, we assume that airfares are a function of the level of competition, z, where a greater value of z corresponds to a more competitive market. At a price P(z), an airline will produce Q units of transportation, with a level of safety s per unit of transportation, where s is a scalar such that $s \in (0, 1)$,

[12]Such cooperation has contributed to the technological advancements both in aircraft and infrastructure and has also led to a convergence of cockpit procedures and an implementation of Standard Operating Procedures (SOP) worldwide (Skybrary, 2018)

$s = 0$ if it there is no safety at all, and if $s = 1$ if there is perfect safety. A firms quantity of transportation provided function Q is increasing in safety and decreasing in price. The cost function increases with quantity provided, and with safety (for example through training, maintenance, and aircraft add-ons). We also assume that the cost of an accident D is a function of safety s. The expected airlines profit function, denoted by Π, can be written as:

$$\Pi = P(Z)Q - C(s, Q, Z) - QD(s, Q) \tag{1.1}$$

The cost also varies with the level of competition in several aspects. On one hand, competition will increase costs, for instance, by decreasing firms wage bargaining power, thus raising wage costs (Sleiman, 2021). Similarly, a more competitive market may reduce existing airlines size, which will constrain reduce their economies of scale on items such as kerosene, spare parts, and meals on board. On the other hand, the greater competitive intensity will push companies to become more creative and efficient, which will cut costs, such as in the paper of Kennet (1993) that showed how after deregulation, airlines have cut engine maintenance costs[13]. Furthermore, the analysis of the effect of competition on cost can be taken a step further. Most economists agree that competition plays a significant role in attaining efficient allocation of resources, often formalized by the notion that a competitive equilibrium is Pareto optimal. One additional notion brought by (Hart, 1983) is that competition induces discipline, which in turns reduces managerial slack. This notion supplements the work of (Winter, 1971), who had modeled competition as a form of natural selection. In his model, inefficient firms experience losses that forces them to find new techniques that are cost improving, which will lead firms to efficiently allocate resources in the long run. In similar lines of research, (Hermalin, 1992; Schmidt, 1997) discuss how competition induces business stealing effect and scale effect. The business stealing effect occurs when firm-level demand functions are elastic have a lower cost, they win over competition. In a competitive market, firms are price takers, firms with higher costs have an increase marginal value in decreasing

[13]There was no compromising safety found

their costs. The scale effect occurs due to an increase in competition, when at least one rival firm charges a lower price, causing the firm to experience a drop in market share and in profits. As a response, the firm is pushed to find cost saving solutions to be able to match its price to be competitive.

Consider R to be the additive risk premium such that for a utility function U, $U[E(\Pi) - R] = E[U(\Pi)]$. With the assumption of normally distributed returns, we can state the firm's maximization problem under the Arrow-Pratt certainty equivalence as:

$$\max_{s} E(\bar{\Pi}) - R\left(E(\bar{\Pi}), Var(\bar{\Pi})\right) \tag{1.2}$$

Here, the bar on $\bar{\Pi}$ signifies expected profits. From this equation, we can see that not just risk-averse, but risk-neutral firms will invest in safety. One assumption in profits is that $\bar{\Pi}_Z \leq 0$. We can say that for a fixed cost borne by an accident, the variance of profits depends on the the level of competition and safety: $Var(\bar{\Pi}) = f(s, Z)$, where s is the only variable that the airline can control. Here, s is a measure of safety that takes into account both frequency and severity of accidents. We can therefore rewrite the firm's maximization problem:

$$\max_{s} \bar{\Pi}(s, Z) - R(\bar{\Pi}, s) \tag{1.3}$$

From here on, the subscripts denote the variable with respect to which the partial derivatives were taken.

Taking first order conditions for a maximum, we get:

$$\bar{\Pi}_s - R_{\bar{\Pi}}\bar{\Pi}_s - R_s = 0 \tag{1.4}$$

For simplicity, we can restrict ourselves to the risk-neutral firms, given that some of them can absorb the shock, in which case we have $R = 0$. We now have a simplified equation for our first order condition:

$$\bar{\Pi}_s = 0 \tag{1.5}$$

To focus on the relationship between safety and competition, we consider the effect of changes in safety and competition on profits. We perform the comparative statics analysis by total differentiation of the first order conditions with respect to safety and competition:

$$\left[\bar{\Pi}_{sZ}\right] dz + \left[\bar{\Pi}_{ss}\right] ds = 0 \tag{1.6}$$

We can rearrange the terms, we get an expression of $\frac{ds}{dz}$:

$$\frac{ds}{dz} = -\left[\bar{\Pi}_{sZ}\right]\left[\bar{\Pi}_{ss}\right]^{-1} \tag{1.7}$$

This can be rewritten as:

$$\frac{ds}{dz} = -\left[\bar{\Pi}_{sZ}\right][SOC]^{-1} \tag{1.8}$$

where SOC is always negative[14]. Hence, we only need to examine the sign of the first bracket.

Since for a risk-neutral firm $R = 0$, we have:

$$sign\left(\frac{ds}{dz}\right) = -\frac{sign\left(\bar{\Pi}_{sZ}\right)}{sign\left(SOC\right)} = sign\left(\bar{\Pi}_{sZ}\right) = sign\left(C_{sZ}\right) \tag{1.9}$$

We can see that the effect of competition on safety depends on the sign of the cross derivative of the cost function with respect to safety and competition. This comes down to understanding how the cost of providing an additional unit of safety varies with the level of competition. Airlines can provide additional safety by investing in newer fleets (or fleet equipment upgrades that are optional), hiring more qualified pilots, providing additional safety training and resources to crew members, investing in flight support (with dispatchers, meteorology) with safety departments, and better maintenance plans.

[14] Our objective function (profits) is concave.

There are many ways in which the cost of safety will increase with a more competitive market. As the market becomes more competitive, fleet investments become more expensive as airlines have a smaller bargaining power. Wages of specialized personnel rises, thus making the acquisition of human resources more expensive. The cost of providing more training may remain constant for airlines that do it all in house but could rise for small airlines that outsource a portion of it (such as to simulator centers). Therefore, in some dimensions, the cost to provide additional safety increases with competition.

Meanwhile, there are other ways in which the cost of safety will decrease with competition. Market forces also push companies to be more creative in how they provide safety. For instance, as the market becomes more competitive, there is greater marginal return to using big data. One common application is for airlines is to use machine learning in predictive maintenance to simultaneously cut costs and improve safety (Bree, 2009; Oh, 2017). Predictive maintenance is often described as "the intelligent way to maximize machine availability." By anticipating failure, maintenance departments can optimize schedules and plans to keep costs low. Similarly, using flight data, airlines analyze problems, included safety related ones, and come up with solutions such as updates of flight procedures, installation of optional safety gadgets (Oh, 2017). A more competitive market is more conducive to fostering such innovation (Vives, 2008).

The actual sign is an empirical question that we examine next in the paper. Given that we do not observe safety, the proxy we use is accidents. Furthermore, we will be using the Herfindahl index as a proxy for competition. Hence, the probability of an accident is a function of safety. The objective is to examine how the probability of an accident varies with competition. Specifically, we will examine how the severity of injuries related to accidents varies with competition. Since the probability of an accident and the severity of an injury is a monotonic function of safety, we can restrict our problem the problem to understanding the relationship that exists between safety and competition.

1.3.2 The Model

Similarly to Phillips and Talley (1996), this paper will look at the conditional probability of severity given the occurrence of an accident. Hence, the probability of occurrence of a given level of severity for an accident is the product of the probability of an accident with the probability that the level of severity occurs, conditional on the fact that an accident has occurred. Let A denote accident and I denote injury. Then the former can be mathematically expressed as:

$$P(A \cap I) = P(A)\, P(I|\, A) \tag{1.10}$$

In February 2009, Colgan Air Flight 3407, marketed under Continental Connection, crashed and killed all 49 people on board. Since then, 8 billion passengers have been flying on U.S. carriers without a fatal crash occurring. Such improvements are due to the collaboration of federal regulators, industry executives, and unions stepping in after a few fatal crashes in the 1990's. Data sharing played a big role in the cooperation among different parties. Aircraft and ground technology leaps were substantial, such as radar and cockpit technologies, reliability of engine and electrical systems. Had there not been any improvements, with the former accident rate of the early 1990's, today we would be seeing at least one crash a week. Over the past two decades, accidents have been on average less severe: there are fewer fatalities and less severe aircraft damages. Nowadays, aircrafts on the ground are more at risk of being involved in an accident than in the air. (Pasztor, 2021).

Let's now elaborate on how the NTSB classifies the intensity of accidents, first by looking at how aircraft damage is measure, then by looking at how injuries are accounted for. There are four levels of damage: no aircraft damage, minor damage, substantial damage, and destroyed. Substantial damage is damage that "adversely affects the structural strength, performance, or flight characteristics of the aircraft, and which would normally require major repair or replacement of the affected component." Minor damage is a "damage that neither destroys the aircraft nor causes substantial damage." An aircraft is considered destroyed if "the aircraft is not repairable, or, if repairable, the cost of repairs exceeds 50% of the cost of the aircraft when it was new" (Skybrary, 2017).

Turning our attention to injuries, there are also four levels of injuries dataset: fatal injury, serious injury, minor injury, and no injury. A fatal injury is "an injury that results in death in the accident itself, or up to 30 days after the accident." A serious injury is "an injury that requires more than 2 days of hospitalization up to 7 days after the accident. Fracture of any bone (except simple fractures of the toes, fingers, or nose). Serious injury also include injury to an internal organ, any muscle or tendon damage, any second- or third-degree burn, or any burn covering more than 5 percent of the body." A minor injury is "an injury that requires less than 2 days of hospitalization up to 7 days after the accident." (Skybrary, 2017). We also combine serious injury with minor injury to create the non-fatality variable. Our injury variable groups all kinds of injuries into a single dependent variable.

Since accidents have been less severe over time, there is a decreasing number of fatalities, as explained above. Most injuries are non-fatal. We can see from the graph (available in the appendix) that plots the cumulative distribution on injuries that for flights involved in an accident, there is nearly 90% are not fatally injured. That number is 73% for non-fatal injuries. On average, we have 0.82 non-fatal injuries and 0.56 fatal injuries per accident, bringing the average total injuries per flight to 1.38. Hence, we choose to make our dependent variable, injuries, account for all types of injuries, both fatal and non-fatal.

Since a more severe accidents are both more damaging to the plane and more harmful to passengers, there is a positive relationship between the severity of aircraft damage and injury. We can therefore specify the following equation:

$$I = F_1(D) \tag{1.11}$$

where D is a discrete variable for Damage, reported by severity level, and I is the injury count.

As noted by Phillips and Talley (1992) an aircraft's accident severity is a function of both airline safety investments and operating conditions. Safety investments are as the name suggests, investments to increase the safety of the airline operations. Hence, greater safety investments should reduce both the likelihood and severity of an accident. Examples include investing in human capital, such as by hiring more experienced pilots, mechanics, flight dispatchers, etc. Operating conditions contains both external and internal factors. Weather and market conditions, that exhibit market pressure on airlines are external factors, while internal factors including training, updating procedures, and crew scheduling policies[15]. The former would require investments in developing and implementing new technologies or improved regulation; the latter is directly under the airlines control. Hence,

$$D = i(airline\ safety\ investments,\ airline\ operating\ conditions) \tag{1.12}$$

We substitute the Damage equation D into F_1 to obtain the reduced-form model equations:

$$I = F_2(airline\ safety\ investments,\ airline\ operating\ conditions) \tag{1.13}$$

By estimating equation F_2, we will be able to examine how airline safety investments and airline operating conditions affect the number of people injured on board of an aircraft involved in an accident.

1.3.3 Variables

In a cockpit, the Pilot in Command 1 (the captain) has the highest authority followed by the Pilot in Command 2 (the first officer). Airplanes can be commanded by one pilot for small taxi planes, to as many as four pilots for an ultra-long flight (generally over twelve hours). Since investment in hiring more experienced pilots is a safety investment, we include the variable *Captain Experience*, which is the total cumulative hours of flight experience the first pilot in command of the flight has, measured in thousands of hours. Due to a large amount of missing data on the second pilot in command (also known as the co-pilot or first officer), we would lose many observations by including the variable in the model. Since the captain has the most crucial role during a flight, particularly in decision making and managing a crisis, it is a small loss of information to omit

[15] that can affect to crew fatigue

the first officer's hours information. More experience allows pilots to assess risks better, manage stress, as well as to make sounder judgment calls, and more appropriately handle the aircraft. A more experienced pilot will conduct the flight in a manner that should reduce the severity of an accident or incident, which is directly related to the injury and fatality count.

In 2008, the Fair Treatment for Experienced Pilots Act has raised the mandatory retirement age for FAR Part 121[16] pilots from 60 to 65, partially due to the beginning of a large retirement wave. In light of the ongoing debate regarding further raising the mandatory retirement age to 67 to dampen the pilot supply shortage, we add the variable *Age*, which is the pilot age. While an older pilot has more experience, his or her mental sharpness may diminish.

Aircraft Weight is the size of an aircraft, measured by its weight in ten thousand pounds. Size can be an essential factor since larger aircraft are not as affected by degraded weather conditions[17]. Therefore, there could be a negative relationship between size and the severity of the accident. *Aircraft Age* is the age of the aircraft, measured in the number of cumulative flight hours it has, measured in ten thousand hours. Older aircraft are more likely to break down, Partially because as it ages, it becomes more difficult to predict when a part will breakdown or be due for maintenance. It can be hypothesized that more frequent aircraft mechanical inspections will decrease the probability of a mechanical failure, which can sometimes compromise safety, and therefore the severity of an accident or incident. Meanwhile, recent advances in predictive maintenance have reduced the probability of mechanical failures using big data (Korvesis, Besseau, and Vazirgiannis, 2018).

Turning our attention to airline operating conditions, we start with some variables on flying conditions. When the weather is clear enough, and the pilot can clearly see where he is going, a flight is performed under visual meteorological conditions. When the weather degrades, such as through fog, rain, or haze, the flight is being conducted under instrument meteorological conditions, which requires the pilots to make reference to instruments primarily. Hence, in the latter case, a visual approach for landing is not permitted. The indicator variable *Favorable Flying*

[16] FAR Part 121 are schedule operations (usually with larger aircrafts) and FAR Part 135 are unscheduled operations (usually smaller planes, such as a 10 seater).

[17] Larger aircrafts are more stable during windy weather conditions

Conditions equals one when the flight is being conducted in visual flying condition and zero otherwise[18]. A factor that affects visibility is whether or not the flight happened during the day or night time. During the night time, the reduced visibility provides additional difficulty operating an aircraft that is undergoing a complication. The indicator variable *Dark Flying Conditions* equals one when the flight is being conducted during the night and zero otherwise. Hence, we expect that *Favorable Flying Conditions* to have a negative relationship with accident severity and *Dark Flying Conditions* to have a positive relationship.

Our last variable related to airline operating conditions is *Last 90 Days*, which is the cumulative number of hundred hours the captain has flown during the past 90 days as a proxy for fatigue. While Phillips and Talley (1996) use the frequency of aircraft landings during the last 90 days, this data is not available anymore. They argued that takeoffs and landings are the most stressful part and therefore cause more fatigue, thus short haul pilots are subject to more fatigue. However, we disagree. Long haul pilots who perform fewer takeoffs and landings still fly the same number of hours but instead have to deal with jet lag, which is burdensome on the body in its own way. We expect to find that there is a positive relationship between *Last 90 Days* and the severity of an accident. We create an interaction variable of *Age* and *Last 90 Days*, as it is plausible that older pilots may be affected differently to the amount of hours flown in the last 90 days than younger ones.

Finally, we have our measures of competition, which are specific to FAR Part 121 carriers. First, we start by explaining the Herfindahl-Hirschman Index HHI, which is considered by many economists as a superior index. Government agencies such as the Federal Reserve Bank, the Department of Justice employ this measure. To calculated the HHI for passenger carriers, we sum the squared percentage of passengers each airline carries in the market on a monthly basis Specifically, the formula is $HHI = \sum_{i=1}^{n}(MS_i)^2$ A more concentrated market means that it is closer to a monopoly, causing the index to become larger. A pure monopoly has an HHI index of 10,000; a market that comes closer to perfect competition, will have an HHI index getting closer to zero. We proceed with the assumption that the United State is a single market and that all airlines compete to obtain a greater market share of that market. As each FAR Part 121 carrier has its own hub,

[18]Details of visual flight rules are available at ICAO Annex 2

they each compete to bring passengers from one point to another and try to expand to capture the largest market share possible. Then, we have Concentration Ratio 4, and 8, which are computed by summing the market shares of the top 4 and 8 airlines respectively. Since these ratios cut out firms, they do not offer a comprehensive picture of the industry. Moreover, the HHI takes into account the sizes of each firm. For example, suppose two markets each have 10 firms with the following markets shares: two firms with 20% and the rest with 10% in the first market and two firms with 35%, two firms with 10%, and the rest with 2.5% for the second market. Each market will have an HHI of 1,400 and 2,675 respectively. For the reasons mentioned, concentration ratios are considered an inferior measure of competition, but still provide some useful insight of the market. Government agencies that use the HHI index consider markets with an HHI below 1,500 as unconcentrated, markets with an HHI between 1,500 and 2,500 as moderately concentrated, and markets with an HHI above 2,500 as highly concentrated. Instead of measuring market concentration, we want to measure market competition. To do so, we use the framework of (Boydstun, Bevan, and Thomas III, 2014) to create a variable *Competition* by subtracting *HHI* from the maximum value of *HHI*, $10,000$, which is the opposite of concentration. With this new definition, a value of $8,500$ or greater is competitive, a value between $7,500$ and $8,500$ is moderately competitive, and less than $7,500$ is uncompetitive. The sign of these three variables is not predictable: on the one hand, a more competitive market may force airlines to cut costs, such as maintenance costs, or make work conditions more stringent which would affect employee morale, hence have a negative impact on safety. On the other hand, a highly competitive market leaves little mercy for a serious accident such as crash, particularly nowadays that they are rare and large media attention. Thus, airlines have an incentive to maintain high safety standards, as a mistake would be costly to their image. We perform the same operation for Concentration Ratio 4 and Concentration Ratio 8 variables: we create a competition ratio variable by subtracting the Concentration Ratio from 100. This allows us to see how much market share is left for competition instead of how much market share is already taken. Our summary statistics will provide the raw *Competition* numbers; in our regression we use the standardized variable.

1.3.4 Model Specification

Since our outcome is a count of people on board that fall into one of several categories, we estimated a negative binomial regression. Because a negative binomial distribution is a mixture between the Gamma and Poisson distribution, that under certain conditions converge towards a Poisson distribution, we therefore provide a succinct revision of the theory of the Poisson regression to introduce the Negative Binomial model as provided by (Greene, 2008). Since the other models provide poor fit, we choose to provide results of the most suited model, the Negative Binomial regression.

The regression specification for the Poisson regression is:

Prob[Y=$y_{it}|x_{it}, x_t$] = $\dfrac{exp(-\lambda_{it})\lambda_{it}^{y_{it}}}{\Gamma(1+y_{it})}$,

with,

$\lambda_{it} = exp(\beta_0 + \beta_1 X_{it} + \beta_2 Competition_t + \alpha_i + \tau_t)$

Where x_{it} is the vector of control covariates presented above for airline i at time t, $Competition_t$ is a monthly measure, α_i is the airline fixed effect, τ_t is the year fixed effect, and ϵ_{it} is the idiosyncratic error[19].

In the Poisson model,

$$E[y_{it}|x_{it}, x_t] = \lambda_{it},$$

and

$$Var[y_{it}|x_{it}, x_t] = \lambda_{it}.$$

But since in our data, as in many cases, has over-dispersion, we employ the negative binomial model:

$$E[y_{it}|x_{it}, x_t] = exp(\beta_0 + \beta_1 X_{it} + \beta_2 Competition_t + \alpha_i + \tau_t + \epsilon_{it}) = h_{it}\lambda_{it},$$

[19] variables Y_{it} and X_{it} are from data collected from a specific day, unlike Competition which is monthly.

where $h_{it} = exp(\epsilon_{it})$ has a $G(\theta, \theta)$ distribution with mean 1 and variance k;

$$f(h_{it}) = \frac{\theta^{\theta} exp(-\theta h_{it}) h_{it}^{\theta-1}}{\Gamma(\theta)}, h_{it} \geq 0, \theta > 0$$

The marginal negative binomial distribution below is obtained after h_{it} is integrated out of the joint distribution,

$$Prob[Y = y_{it}|x_{it}, x_t] = \frac{\Gamma(\theta + y_{it}) r_{it}^{\theta} (1 - r_{it})^{y_{it}}}{\Gamma(1 + y_{it})\Gamma(\theta)}, \tag{1.14}$$

with $\theta > 0$, and $r_{it} = \theta/(\theta + \lambda_{it})$

We thus obtain:

$$E[y_{it}|x_{it}, x_t] = \lambda_{it}$$

and

$$Var[y_{it}|x_{it}, x_t] = \lambda_{it}[1 + (1/\theta)\lambda_{it}] = \lambda_{it}[1 + k\lambda_{it}]$$

Where $k = Var[h_{it}]$.

1.4 Data and Results

The data for all variables except the Inverse HHI index comes from the NTSB database; the later comes from the Bureau of Transportation Statistics (BTS) form 41 T-100[20]. Both datasets are public.

Aircraft accidents and serious incidents are rare occurrences that must be reported to the NTSB, but non-serious incidents do not have to be reported (AOPA, 2016). Therefore, information collection on accidents is more reliable than on incidents. Hence, it is easier for airlines to avoid disclosing incidents than accidents. According to the NTSB's definition, an accident is an occur-

[20]The Air Carrier Statistics database, also known as the T-100 data bank, contains domestic and international airline market and segment data. Certificated U.S. air carriers report monthly air carrier traffic information using Form T-100. The data is collected by the Office of Airline Information, Bureau of Transportation Statistics. The tables in this database provide domestic market, domestic segment, international market, international segment, combined table for domestic and international market, combined table for domestic and international segment data by certificated U.S. air carriers. This database is frequently used by the aviation industry, the press, and the legislature to produce reports and analyses on air traffic patterns, carrier market shares, as well as passenger, freight, and mail cargo flow within the aviation mode. The data is conducive to producing carrier load-factors, but does not contain carrier financial information.

rence associated with the operation of an aircraft that takes place between the time any person boards the aircraft with the intention of flight and all such persons have disembarked, and in which any person suffers death or serious injury, or in which the aircraft receives substantial damage. An incident is an occurrence other than an accident, associated with the operation of an aircraft, which affects or could affect the safety of operations (CFR-830.2, n.d.).

After an accident or incident occurred, the NTSB promptly sends a team of multiple specialists of different expertise on site for investigation[21] (NTSB, n.d.). An example of an accident with no injuries is an aircraft that flew over an active volcano, landed safely, but the aircraft must be written off. The following is a non-exhaustive list of examples of incidents provided by the Cornell Law School's Legal Information Institute (CFR-830.5, n.d.):

- Inability of any required flight crew member to perform normal flight duties as a result of injury or illness
- Failure of any internal turbine engine component that results in the escape of debris other than out the exhaust path
- Flight control system malfunction or failure
- Controlled in-flight fire
- Damaged wing-tips

Table 1[22], which constitutes the summary data of FAR Part 121 carriers, reveals that the mean of Damage is 2.024, which implies that on average, the aircraft involved in the accidents received minor damage. Furthermore, among those aboard the flights involved in the accidents about 97 percent were not injured. The dataset contains 291 observations with no damage, 213 with minor damage, 327 with substantial damage, and 19 destroyed. Captains have an average of $11{,}620$ hours

[21]The NTSB makes the data regarding the accidents and incidents investigated publicly available in Microsoft Access format.

[22]We use ratios instead of counts of injuries to provide a better understand of injuries: while a number of injuries may seem arbitrarily large, it could be relatively small in proportion to the airplane size (number on board)

of experience and have flow 176.2 hours in the last 90 days, which is 58.73 hours per month. The average age of aircrafts is 27,940 hours, with an average weight of 160,900 pounds (80.45 tons)[23]. Average last inspection was done about 659 flight hours before the accident. Moreover, about 24% of the flights were operated in dark flying conditions, and 82% of flights were operated during visual flying conditions. With a mean *Competition* value of 9071.8 ranging from 8749.3 to 9277.1, the market is considered competitive.

Table 2 presents the mean of each level of injury by aircraft damage severity. Aircraft that were involved in one accident and were not damaged resulted in almost no fatalities, an average of 2.78 percent of people on board suffering non-fatal injuries, while an average of 97.2% of people on board were not injured at all. Accidents that sustained minor damaged had, on average, 0.04 percent fatal injuries, 0.84 percent non-fatal injuries, and the remainder were non-injuries. On average, aircraft that were severely damage had 0.01 percent fatal injuries, 0.57 percent non-fatal injuries, and 99.12 percent non-injuries. Airplanes that were destroyed in an accident have, on average, resulted in 93.77 percent fatal injuries, 5.23 percent non-fatal injuries, and 1 percent no injuries. Mostly, injuries occur if an accident causes an aircraft to be destroyed.

Equation (13) is estimated through the equation (14) and is presented in Table 3 in columns one through three. Regressions control for year and airline fixed effects, with standard errors clustered at the airline level. Table 3A, 3B, and 3C present negative binomial regression results with FAR Part 121 operators[24] to examine the effect of market competition on safety of scheduled commercial airlines through the Inverse HHI, Inverse CR8, and Inverse CR4. Tables 3B and 3C show results with Inverse CR8 and Inverse CR4 respectively in the appendix.

As expected, experience, measured by the captain's total hours of flight experience decreases the count of suffering from injuries with one and five percent significance. Dark flying conditions affect, which is a proxy for degraded flying conditions, negatively affect safety at one percent significance.

[23]This corresponds to a medium haul aircraft.

[24]As the two types of operations FAR Part 121 and 135 are very different, and our primary focus is on scheduled operators which carry most passengers transported in the U.S. Airspace, we do not present results for Part 135 operations.

When looking at the effect of a captain's fatigue through the proxy of the number of hours flown in the last 90 days, our results, significant at five percent, suggest that more flight hours in the last 90 days correspond to an increase in juries up until the turning point age of 35.5 and 37.5 for regressions (1) and (3) respectively and then a decrease in injuries. Meanwhile, while just looking at age, our results in regression (2) show that age increases injuries until the turning point age of 46.4 and decreases after. Hence, older pilots after a threshold, like more experienced pilots, are safer.

Regression results show that greater competition will increase the count of people on board that will suffer from any kind of injury conditional on having an accident. Specifically, from Table 3A, we see that the parameter estimate of *Competition* is positive and significant at 5%, which is confirmed in Table 3B and Table 3C for the parameter estimate of Competition Ratio 8 and 4 respectively. A one standard deviation increase in *Competition* increases the odds of receiving any injury in an accident by 447% to 465%. As the top 8 firms increase their market share by one standard deviation, there is an increase in the odds of receiving any injury by 45% to 47%. Furthermore, when the top 4 firms increase their market share, we find that the parameter estimate is significantly positive. These findings imply that a less competitive environment allows firms to increase their safety because they have a stronger ability to use economies of scale to cut cost and reinvest in safety[25].

Hence, there we find evidence that a less competitive market will increase safety. This result is consistent with the findings of (Shashoua, Sridhar, and Mittal, 2017). As airlines charge higher prices on routes that two airlines competed on before their merger (Shen, 2017), the higher profits are then reinvested into safety. The of significance of this results imply that more competition has an adverse effect on safety. Since safety is not observed by consumers, under a less competitive environment, the pressure to under-provide it diminishes; firms are more capable to invest in safety measures, such as training and aircraft technology upgrades.[26] to name a few. Investments in the

[25]Cost cutting measures are discussed in Section 3

[26]Air France flight 447 had crashed an A330. After investigation, the airline decided to invest in pitot tubes for their A330, as it may have prevented the crash

aviation sector require large capital and labor investments that are not easily adjustable in the short run. Under such conditions, the lessening of financial pressures induced by market forces enable airlines to operate more safely.

1.5 Discussion

We conclude our study of the effects of competition on market safety by addressing a few points. First, our results confirm previous research by finding that poor flying conditions, such as dark skies, affect air safety. Specifically, poor flying conditions increase the count of passengers and crew injured. We also confirm that that total pilot experience decreases the proportion of people injured on board for Part 121 carriers.

Second, we see that when there is an increase in additional hours flown in the last 90 days, the count of injuries falls after the turning point age of 37.5. Thus, as pilots get older, the effect of fatigue causes them to make less accidents. A possible explanation is that over time, as pilots move up in the seniority, they are more likely to get the flights that they bid for. Hence, with their experience and seniority, they make a schedule that better fits them. This result is important because the FAA has enacted PL111-216 in 2010 after the Colgan Air crash that would impose Part 121 airlines to follow specific rules to curtail pilot fatigue[27]. Airlines should investigate the effects of fatigue based on schedules and update their scheduling mechanism to make sure that better rest if provided for those with little seniority.

Third, in light of an ongoing debate in the aviation world regarding extending mandatory pilot retirement age, we find evidence that older pilots provide are safer. While cognitive skills may decline over time, the experience gain makes up for it[28]. This is particularly interesting for two reasons. First, since back in 2008, the mandatory retirement age of Part 121 operators had been moved from 60 to 65[29]. There were concerns that extending the retirement age would have adverse

[27] Quoting directly from the act: the Administrator of the Federal Aviation Administration shall issue regulations, based on the best available scientific information, to specify limitations on the hours of flight and duty time allowed for pilots to address problems relating to pilot fatigue. https://www.congress.gov/111/plaws/publ216/PLAW-111publ216.pdf

[28] As planes are becoming more automated, flying has shifted to become more about planning and decision making.

[29] "The legislation, known as the Fair Treatment for Experienced Pilots Act, raised the upper age limit from age 60 to

safety consequences, which we now see is not the case. Second, since nowadays there appears to be a potential pilot supply shortage, authorities have discussed potentially extending the retirement age to 67. Due to the evidence that shows that older pilots can provide additional safety through their experience, this paper provides initial evidence in favor for extending the retirement age to 67.

Fourth, we find evidence that a less competitive market will decrease the odds of being injured in an accident. Airline safety investments are costly; hence a less competitive market allows as previous research by (Shen, 2017; Gerardi and Shapiro, 2009) has shown, firms to charge higher prices that yield greater profit margins, which can be reinvested into safety. Hence airlines reinvest into safety a portion of their excess profits gained in a less competitive environment. Potentially, mergers have had some positive impact on safety. As airlines often have difficulties to survive and policy makers have struggled with the question of approving airline mergers, particularly because of its effects on airfares, our results suggest that it is advisable to approve a merger when considering the safety perspective. While it may be tempting to think about putting barriers to entry, we must be careful about which are put into place. We have several policy recommendations to improve safety and make passengers aware of the unobserved safety level. First, we recommend that the FAA create a new SPI that measures the operation safety performance of the U.S. airline industry not solely based on frequency but also taking into account the severity of accidents. According to the ICAO's Safety Management Manuel, there is no single SPI that is applicable to all cases, so the more the better (*Doc 9859* 2018). This would allow the FAA to have a new tool to monitor safety from a new dimension. Currently, the FAA uses an SPI that measures safety as a "rate of fatalities per 100 million person on board", thus does not yet take into account severity nor aircraft damage. Second, we recommend making an ex-ante SPI for each airline, by performing more audits on areas such as training, maintenance, and scheduling. Both of these scores should be made public and displayed by both airlines and travel agency websites. Such a practice will allow passengers to be aware of the safety level of each airline, which will help close the asymmetry of information gap.

age 65. The legislation became effective December 13, 2007. The intended effect of this action is to update the Code of Federal Regulations to reflect the recent legislation" https://www.federalregister.gov/documents/2009/07/15/E9-16777/part-121-pilot-age-limit

Lastly, we encourage the implementation of congestion pricing. Congestion pricing 33 is a mechanism where landing fees are a function of the level of congestion at the airport instead of the current practice where airlines pay a fee based on the empty weight of the aircraft. Consequently, congestion pricing will cost more during peak hours. Since most accidents happen near landing and take-off strips, congestion pricing which will reduce the amount of flights around peak times will have an effect of reducing traffic density, thus reducing accident frequency and severity.

Table 1.1: Summary Statistics

	Variable Definition	Min	Max	Mean	SD
Captain Experience	Captain total flight experience (1,000 hrs)	1.595	38.58	11.62	5.978
Last 90 Days	Captain last 90 days of flight time (100 hrs)	0.12	3.1	1.762	0.5268
Age	Captain age	24	64	46.21	9.456
Aircraft Age	Aircraft age in (10,000 hrs)	0.0031	10.35	2.794	1.987)
Aircraft Weight	Aircraft weight in (10,000 lbs)	0.28	213.3	16.09	15.56
Dark Flying Conditions	Dummy variable for dark flight conditions	0	1	0.2419	0.4283
Favorable Flying Conditions	Dummy variable for visual flight conditions	0	1	0.8203	0.3840
Injury	Percent onboard with any injury	0	265	1.3836	7.009
Damage	Damage level of aircraft	1	4	2.024	0.8939
Competition	Inverse Herfindahl Hirschman Index	8749.3	9277.1	9071.8	147.13
Competition Ratio 8	Inverse Concentration Ratio 8	13.52	33.58	23.82	6.024
Competition Ratio 4	Inverse Concentration Ratio 4	32.52	55.27	47.04	5.849
Observations	850				

Table 1.2: Injury Summary Statistics by Damage Level

	Aircraft Damage				
	Mean	None	Minor	Severe	Destroyed
Injuries					
Non-Fatal Injury	0.0152	0.0278	0.0084	0.0057	0.0523
	(0.0524)	(0.0682)	(0.0354)	(0.0269)	(0.1585)
FatalInjury	0.0124	0.0001	0.0004	0.0001	0.9377
	(0.1092)	(0.0009)	(0.0047)	(0.0004)	(0.2061)
No Injury	0.9695	0.9722	0.9841	0.9912	0.0100
	(0.1321)	(0.0681)	(0.0908)	(0.0613)	(0.0412)

The numbers provide mean probability values.
Corresponding standard deviations below in parenthesis.

Table 1.3: Negative Binomial Estimation Results - Inverse HHI

VARIABLES	(1) Injury Count	(2) Injury Count	(3) Injury Count
Captain Experience	-0.0870***	-0.0826**	-0.0829**
	(0.0336)	(0.0356)	(0.0349)
Last 90 Days	1.840	-0.381**	1.265
	(1.166)	(0.187)	(1.097)
Age	0.0960	0.346*	0.361
	(0.0722)	(0.210)	(0.220)
Age x L90D	-0.0490*		-0.0356
	(0.0266)		(0.0242)
AGE Squared		-0.00372	-0.00320
		(0.00232)	(0.00225)
Aircraft Weight	0.0303*	0.0339*	0.0329*
	(0.0160)	(0.0174)	(0.0178)
Aircraft Age	-0.0743	-0.0789	-0.0764
	(0.0980)	(0.0956)	(0.0958)
Dark Flying Conditions	0.931***	0.872***	0.938***
	(0.295)	(0.312)	(0.298)
Favorable Flying Conditions	0.406	0.343	0.338
	(0.403)	(0.432)	(0.408)
Competition (Inverse HHI)	1.727**	1.731**	1.699**
	(0.774)	(0.811)	(0.818)
Observations	850	850	850
Pseudo R-squared	0.1625	0.1636	0.1645

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Variables explained: Captain Experience is the total experience of the captain in thousands of hours. Last 90 Days is the total number of (hundred) hours the captain has flown the past 90 days. Age is the age of the captain. Aircraft Weight is the aircraft weight in thousands of pounds. Aircraft Age is the aircraft age in thousand of flight hours. Dark Flying Conditions is a dummy variable equal to 1 if the flight is operated under dark flying conditions, and 0 otherwise. Favorable Flying Conditions is a dummy variable equal to 1 if the flight is operated under visual flight conditions, and 0 otherwise. Competition is the standardized inverse Herfindahl Hirschman Index.

Chapter 2

Monoposony Power in the U.S. Airline Industry: Are Pilots Underpaid?

2.1 Introduction

The rise in ownership concentration across many U.S. industries has brought renewed attention to the monopsony power of employers and to the lack of bargaining power of workers (Autor et al., 2020; Krueger, 2018). The monopsonistic labor market model predicts that firms have market power in hiring as a result of an upward sloping labor supply curve (Robinson, 1969). An upward sloping labor supply curve provides firms with an incentive to reduce employment and pay workers a wage below their marginal products. In this paper, we investigate U.S. airline monopsony power over their pilots, and bring empirical evidence to the growing policy debate on the effects of employer monopsony power on workers (CEA, 2016, Mellman, 2019).[1]

The U.S. airline industry, which carried about 800 million passengers in 2018, is an interesting case for the study of monopsony power for several reasons.[2] A slew of bankruptcies and mergers has increased market concentration in the airline industry over the past 15 years. At the same time, media coverage points to concerns over labor shortages and safety (Meredith, 2018; Airbus, 2017). There are also reports that airlines have exploited their pilots, especially at smaller and budget carriers, by paying below market wages, and by shifting the training cost to employees (Gall, 2018).

The fact that there are only a small number of commercial airlines operating in the U.S. market hiring from a large pool of potential workers intuitively suggests that airlines have market power.[3] There are several possible theoretical approaches to studying monopsony power. Modern search theory predicts that search frictions lead to wages below the marginal product (Mortensen, 2003). In the context of the aviation industry, we expect firm characteristics and switching costs to be likely causes of frictions. If workers differ in their valuation of firm's non-wage characteristics,

[1] In 2019, the Federal Trade Commission (FTC) held Hearings on Competition and Consumer Protection in the 21st Century, which included three hearings on monopsony power.

[2] https://www.bts.dot.gov/newsroom/2018-traffic-data-us-airlines-and-foreign-airlines-us-flights

[3] See Table C.5 for a list of all carriers in our sample.

firms will be able to set wages. There is considerable variation in airline size, prestige, and along other dimensions, which results in heterogenous quality of airlines as employers. For example, working at a regional carrier is substantially different from working at a legacy carrier. Pilots face significant cost switching costs because benefits that accrue with tenure are non-transferrable.[4] Lastly, firms tend to have market power if their workers are highly-skilled, specialized and lack alternative occupations, which applies to pilots (Link and Landon, 1975; Muehlemann, Ryan, and Wolter, 2013).

We estimate monopsony power in the airline industry by directly estimating the residual labor supply curves facing individual airlines. Estimating the labor supply curve is of course complicated by the fact that we only observe a single equilibrium set of prices and quantities for an airline in a given time period. The resulting simultaneity problem calls for an instrumental variables estimation strategy that provides a demand shifter, as proposed in the seminal work by Wright, 1928. Using the incidence of aviation accidents as an instrument for the number of pilots employed, we can estimate the labor supply curve and the wage elasticity of labor supply. Importantly, we use a firm-level instrument – accidents to an individual airline – to estimate the firm-level (or residual) labor supply. Labor supply elasticity smaller than infinity and wages below the workers' marginal revenue product are evidence for monopsony power. We estimate an *inverse* labor supply elasticity of 2.55 across all airlines, which implies that airlines pay pilots 30.95% below the marginal revenue product.[5] These results suggest that, on average, airlines have monopsony power in hiring pilots.

To further support our finding that airlines exercise market power in hiring, we analyze the relationship between the market concentration, as measured by the (inverse) Herfindahl-Hirschman Index (HHI), and the labor supply elasticity. Over the sample period, market concentration varies considerably as a result of bankruptcies, mergers, and new entrants. As expected, airlines' market power in hiring rises when the market becomes more concentrated.

[4]Seniority is airline specific. All seniority benefits such as compensation, scheduling, and buddy passes improve over time.

[5]A competitive labor market is characterized by an inverse labor supply elasticity of zero.

The existence of great and persistent monopsony power in the heavily unionized aviation industry suggests that unions ability to counter employer market power may have limits. What does this mean for policy-makers and regulators that want to ensure fair labor market conditions? Low-wage workers can be protected by minimum wage laws. Wage floors, of course, do not bite for comparatively high-paid workers such as pilots.

A monopsonistic labor market is not pareto optimal and policy intervention can help reach a second-best outcome. One plausible approach to limiting monopsony power in high-skill labor markets is antitrust enforcement. Historically, antitrust enforcement has been primarily concerned with the impact of a lack of competition on product prices and consumer welfare. Little attention has been paid to labor market power, and airline mergers are no exception[6]. In the past two decades, regulators approved more than a dozen mergers, which cut the number of airlines operating in the U.S. in half. The Department of Justice, presented with the option to challenge mergers, has never cited labor market competition as a concern. These decisions to not challenge mergers is supported by the established norm that markets are considered unconcentrated if the HHI does not rise above 1,500. The U.S. aviation industry has not crossed this threshold between 1995 and 2018. This makes it all the more surprising that we find robust evidence of airlines' ability to set wages, suggesting that a product-market based measure of market concentration, such as the HHI, may be insufficient as a basis for competition policy.

As with other jobs, pilot performance potentially varies with the level of job satisfaction, which in turn is a function of their compensation, job amenities, and other factors. A crucial output of pilot performance is the safety of the aircraft. Pilots bear sole responsibility for the operation of the aircraft and the safety of everyone on board. Passengers are interested in having a pilot that is fit to fly and able to perform optimally. Poor compensation and job satisfaction could thus undermine safety. There is some evidence that pilots are experience high levels of stress and low levels of job security (GOOSE Recruitment, 2020).[7]

[6]https://www.justice.gov/atr/events/public-workshop-competition-labor-markets

[7]Aviation recruiters GOOSE Recruitment and aviation publisher FlightGlobal surveyed pilots and published a report discussing pilot career satisfaction (GOOSE Recruitment, 2020). We will not discuss all the findings. The interested reader is invited to look at the full report at https://www.goose-recruitment.com/the-pilot-survey-2021.

Our finding that pilots are paid below their MRP may contribute to poor job satisfaction among pilots. In turn, we may observe safety improvements as a result of higher wages.

2.2 Monopsony in the Labor Market

2.2.1 Motivation

Much of the work in labor economics relies on the assumption that markets are near perfect competition. In perfect competition, firm-level labor supply elasticity is infinite, and the firm can hire or fire workers without adjusting the wage.[8] Workers are paid a wage equal to their marginal revenue product. In practice, there are many situations with significant labor market frictions and we have reason to suspect that employers have the power to set wages. This is the case in a monopsonistic labor market. Robinson, 1969 first introduced the term “monopsony”, which describes a market with a single buyer. The term monopsony is now commonly used to describe factor markets with a small number of employers that face increasing labor supply curves and, as a result, possess significant market power (technically, an “oligopsony”). A growing body of literature provides empirical evidence on employer market power in various settings, suggesting that monopsonistic markets are by no means an oddity.

2.2.2 The Static Monopsony Model

A firm with monopsony power faces an upward-sloping labor supply curve, which implies that it can pay wages below competitive levels without losing all its workers. This creates an incentive to maximize profits by reducing employment relative to the competitive market, which introduces a wedge between the marginal revenue product of labor and the wage (see Figure 1, distance between w_{mrp} and w_m). The difference between the MRP, and the wage paid by a monopsonist has been termed the “rate of exploitation” and is captured in the form of rent by the monopsonist (Hicks, 1932; Pigou, 2013). It is important to note that the “rate of exploitation” does not tell us how much less workers are paid relative to the case of perfect competition.

[8] Firms are wage takers.

The firm maximizes profits Π as follows:

$$\Pi = R(L) - W(L)L \tag{2.1}$$

where $R(L)$ is the revenue function, L is the quantity of labor, $W(L)$ is the wage rate and $W(L)L$ is the total wage cost.

The first-order conditions yield:

$$R'(L) = W'(L)L + W(L) \tag{2.2}$$

The first-order conditions can be rearranged as follows:

$$\frac{R'(L) - W(L)}{W(L)} = \frac{1}{\epsilon_{Lw}} = \epsilon, \tag{2.3}$$

where ϵ_{Nw} is the wage elasticity of labor supply facing the monopsonistic firm. The static profit maximization problem of a monopsonistic firm provides us with a way to measure monopsony power: We can estimate the (inverse) labor supply curve to a firm and derive the size of the wedge between the marginal revenue product and the wage.[9]

In a review of the literature, Manning concludes that "the elasticity of the labor supply curve facing the firm does not seem to be close to infinite but that it is hard to get a very precise estimate of it (2003)." Generally, estimates of 2-5 are considered reasonable. Estimates in this range imply that employers have a size-able degree of monopsony power: an elasticity of 5 implies that wages are 17% below the marginal revenue product (MRP) and an estimate of 2 implies that wages are 33% below the MRP.[10]

[9] With respect to the standard formula of the wage elasticity of supply, we estimate the *inverse* labor supply elasticity because in our empirical specification we have the $(log)wage$ on the Left-hand-side of the equation and the quantity of labor on the Right-hand-side.

[10] We obtain the exploitation gap by solving the static optimization problem of the monopsonist and empirically estimating the labor supply elasticity. Given a wage of 100 and an estimated elasticity of 2, the exploitation gap of 50 is calculated as follows:

1.

$$
\begin{aligned}
& n\frac{MRP - w}{w} = \frac{1}{\epsilon} \\
\Rightarrow\ & \frac{MRP - 100}{100} = \frac{1}{2} \\
\Rightarrow\ & MRP = 150
\end{aligned}
$$

2.2.3 *Literature Review*

Economists have studied monopsony power in a variety of sectors and with a number of approaches. A handful of papers have been able to estimate firm-level labor supply curves. This includes the work of Falch, 2010 on teachers, Goolsbee and Syverson, 2019 on university professors, Boal, 1995 on coal miners, and Hirsch and Schumacher, 1995, Matsudaira, 2014, Staiger, Spetz, and Phibbs, 2010, and Sullivan, 1989 on nurses. Several of these studies exploit a one-time policy change with differential impacts on average wage across firms to estimate the labor supply curve. Authors typically rely on indirect methods because the data needed to identify classical monopsony power includes firm-level labor demand shifters that are not commonly available. Some authors, for example Falch, 2010 and Goolsbee and Syverson, 2019, identified suitable instrumental variables to directly estimate the residual labor supply elasticity, that is, the labor supply to the individual employer. We follow this approach.

Crémieux and Van Audenrode, 1996 analyze the effect of mergers on the earnings and employment of pilots, flight attendants, and mechanics in the US airline industry between 1971 and 1990. Increased market concentration should increase the bargaining power of the remaining airlines. In contrast, by increasing market share and monopoly power, a merger may increase the total rents, a share of which may or not go to labor. Their results show that mergers had no impact on pilots?? earnings, essentially leaving the question of whether airlines hold monopsony power over pilots unanswered. Although Crémieux and Van Audenrode (1996) show that mergers have no significant impact on pilot employment, we explicitly account for mergers in our analysis because both the time period under consideration (1971-1992 vs 1995-2018) and our identification strategy are different.[11]

Our test of monopsony power centers on estimating the residual labor supply curve facing each airline. Two things are needed to estimate the residual labor supply curve to a firm. First, it requires firm-level data on average wage and quantity. Second, it requires firm-level instruments

[11] See Table C.7 for a list of mergers in our sample period.

for labor demand to get around the reverse causality problem (see, for example, Falch, 2010). In the following sections we present firm-level data on average wage and pilot employment and a labor-demand shifting instrument.

2.3 Background

2.3.1 Pilot Training

The United States has a unique and archaic pilot training system. Originally, the system was designed where military pilots would join airlines after their Navy or Air Force contract had terminated. While this was how the vast majority of pilots were trained, a few went through the private training route. Nowadays, most pilots get training at a flight school. This is due to a few reasons. First, the growth of commercial aviation has grown steadily over the past decades and outpaced the growth in military aviation. Second, the military has been offering more competitive compensation to retain its pilots, hence a smaller percent of military pilots are going to fly for airlines. Unlike the rest of the world, the US has not changed the structure of its pilot training program, and instead made it more cumbersome.

Becoming a pilot is costly, both in terms of the training hours required and the financial cost. In the United States, obtaining all necessary licenses and certificates to work as a commercial pilot costs approximately \$100,000.[12] In response to safety concerns following the Colgan Air regional airline crash in February 2009, the number of flight hours to obtain a Airline Transport Pilot (ATP) certificate have been increased. Specifically, the training hours required to become a regional airline pilot were increased from 250 hours to 1,500 hours (with some exceptions).[13] Flight hours are typically accumulated as a flight instructor, which comes with modest compensation. Flying 80 hours a month, adds approximately two years to complete the required hours.[14] In short, the more stringent training requirements delay labor market entry for commercial pilots by at least two

[12] https://atpflightschool.com/become-a-pilot/flight-training/pilot-training-cost.html. There are no FAFSA loans for flight school

[13] Public Law 111-216, which was enacted on August 1st 2010 https://www.congress.gov/111/plaws/publ216/PLAW-111publ216.pdf

[14] It is an improbable upper bound to reach

years. Once a pilot obtains an ATP, he/she typically joins a regional airline and remains there for four to seven years before joining a carrier that operates larger aircrafts. The following section will provide some light on the career paths. Additional information on the training path is presented in the appendix.

2.3.2 Pilot Career Paths

Let's begin by explaining some fundamental terminology regarding the regulations and structure of the industry. We will present a summary; for a more complete explanation, view the work done by (McGee, 2015). There are two types of commercial flight operations: FAR Part 121, FAR Part 125, and FAR Part 135. FAR Part 121 is for scheduled flight operations, such as when we fly a regional, low-cost, or legacy carrier (these are larger aircrafts). FAR Part 135 operations are for charter flights, such as island hopping, flying to small airports, private jets where seats are sold (these are smaller aircrafts). Both are flying from selling seats to passengers. FAR Part 91 operations are flights that are conducted for personal use through a small single engine plane to a large plane used for FAR Part 121 operations. The highest paid and most prestigious job a pilot can obtain is one at major airline, then at a low-cost airline, followed by one at a regional airline, and lastly at either a FAR Part 135 or 91 operation. Pilot hiring at commercial airlines is based on a point system, where the more points you have, the more likely you are to be hired next. For instance, more total flight hours, more hours on multiengine, more hours of pilot in command [15], having more years of college education earn more points. To reach the goal of flying for a FAR Part 121 operation, there are several requirements that must be met[16]. Since having a college degree is an important component, many earn at least a bachelor's degree[17].

When a pilot gets a job flying an aircraft certified to be operated with two pilots, he or she must obtain a type rating for that specific aircraft to be qualified to operate that specific aircraft. This is the first time that a pilot will learn how to fly with someone else in the cockpit. While this license

[15]Here is the FAA's official definition of PIC: 1. The PIC has the final authority and responsibility for the operation and safety of the flight. 2. Has been designated as pilot in command before or during the flight; and 3. Holds the appropriate category, class, and type rating, if appropriate, for the conduct of the flight.

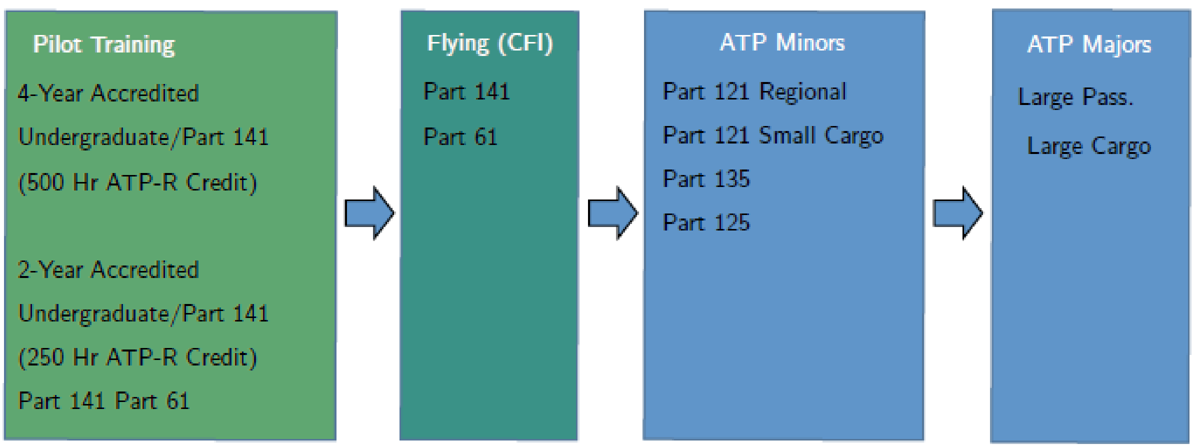
[16]The requirements are airline specific, and mostly revolve around education and experience,

[17]A university degree allows to enter sooner a major airline, and offers alternative jobs in case of being furloughed.

can be obtained without a job, it is usually paid for by the airline. The type rating can either be as Pilot-in-Command (for captains) or Second-in-Command (for first officers). On their first job, pilots start as Second-in-Command.

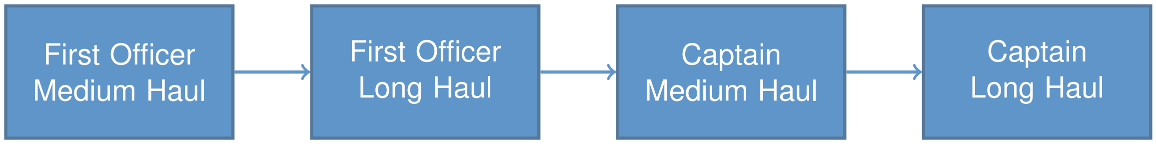
A typical career path for a pilot looks as follows: after the training is completed, pilots remain flight instructors as a career, until they can fly for a regional airline as Part 121. Regional pilots usually stay with the company four to seven years before being able to advance to a major airline or cargo airline that is also Part 121. Military pilots can obtain their ATP with 750 hours and when completing their service can join the major airlines directly instead of entering a regional carrier first.

Figure 2.1: Training and Career Path



When a pilot joins a major airline, pilots usually start as a first officer on a smaller plane, then move on to a larger plane, become a captain on a small plane, and spend the end of their career as a captain on a large plane. Since a pilot's hourly wage is a function of aircraft size and seniority, they try to move on larger planes as quickly as possible. When a pilot joins a low-cost airline, they (usually) just climb up the seniority list since there is just one airplane type; the largest wage increase occurs when the pilot is promoted from first officer to captain. The following diagram shows the career evolution of a pilot joining a major airline:

Figure 2.2: Career Evolution



2.3.3 Pilot Wages

The wage structure of commercial pilots in the United States has multiple components, most of which relate directly to the number of hours worked. Pilots are paid an hourly rate for every flight hour. This rate varies with seniority (number of years they have been with the airline), the type of aircraft (larger and faster aircrafts that generate more revenue warrant a higher hourly rate), and the level of responsibility (captains get paid more than copilots). See Figure C.1 for wages over time and Table C.1 and Table C.2 are examples of compensation tables at Delta Airlines. Contracts specify a minimum of hours, which guarantees base earnings, and overtime pay, for flight hours beyond the minimum.[18] When the flight takes place also affects a pilot's wage: night flights, flights on holidays, and flying during requested time off, are usually paid at a higher hourly rate. Standby pilots, who are on duty and ready to fly in case another pilot cannot fly (i.e. due to sickness), receive a guarantee of productive, paid, hours that day. For example, a pilot that has waited a day on standby, but did not replace a pilot, will be compensated for a given number of hours of productivity as specified in the contract. Further compensation is paid to pilots that perform non-flying duties such as crew repositioning, attending mandatory training course etc. Active pilots that serve as instructors are paid a varying premium for their work.[19] Our outcome variable is the average wage that an airline pays to its pilots. This measure includes all components of compensation discussed above but does not include any benefits the airline may offer.

[18]Delta Airlines, the minimum guarantee is 65 hours of flight per month. The FAA restricts pilots to a total of 1,000 hours a year.

[19]There are different types of instructors. Non-active pilot performing ground instruction work spend most of their time providing theoretical training to pilots in classrooms. Active pilots train pilots in simulators, either for a pilot's first-time training on the aircraft or for active pilots that train to remain legally current on handling normal and abnormal flight procedures. There are also in-flight instructor that continue the pilot's training on the aircraft during normal revenue flights. Lastly, there are examiners that certifies that the pilot meets the required level of competency to perform his flight duty with another qualified pilot on the aircraft.

2.3.4 Unions

As in other industries, commercial airline pilots vote on whether or not they want to join a union. The two largest unions in the United States are the Air Line Pilots Association (ALPA), and Teamsters. Unions represent the pilots and negotiate labor contracts with the airline. Broadly speaking, unions negotiate average wage and work conditions, though contracts are highly complex and often span hundreds of pages. For instance, the union may negotiate specifics of work conditions, such as crew rest times (how many consecutive hours a pilot can fly), restrictions on time zone changes to account for jet lag and the resulting recovery time. Contracts are typically renegotiated every four years and negotiations often last more than a year. Unions and airlines also negotiate amendments while contracts are in force. When incidents and accidents occur, an internal investigation is required to determine the root cause. If work conditions have led to an accident, contracts are amended accordingly, for example to include further scheduling restrictions.

2.3.5 Safety

Safety is a major concern for travelers and has significantly improved over the past decades (Airbus, 2017). Accidents do not happen because of a single mistake or a failure of equipment, but are typically the result of a sequence of unfortunate occurrences, such as equipment malfunction and multiple pilot errors. Studies show that pilot error is the principal cause of accidents, as pilots are supposed to navigate difficult situations (Oster, Strong, and Zorn, 2010). Most accidents happen close to airports, during poor weather or in difficult terrain. We might expect that there is a greater risk of accidents when an airline experiences financial stress, but there is no conclusive evidence to support this. Rose, 1990 shows that lower profitability is correlated with greater a greater accident rate, particularly among small airlines. However, Wang, Hofer, and Dresner, 2013 show that safety investments (that reduce the risk of an accident) are not affected by an airline's financial health. Further, Gaba and Greve, 2019 show that less profitable airlines are more likely to replace older aircraft and modernize their fleet, which not only reduces cost but also increases reliability. In sum, an airlines financial health is not a reliable determinant of safety, and accidents are most likely to happen as result of issues during flight operations.

2.3.6 Competition

We start by introducing the Herfindahl-Hirschman Index, a widely accepted measure, to assess market concentration in the airline industry. The HHI is calculated by squaring the market share of each firm competing in the market and then summing the resulting numbers. See Figure C.1 for HHI over time. For example, for a market consisting of four firms with market shares of 20, 20, 30, and 30 percent, the HHI is 2,600 (202 + 202 + 302 + 302 = 2,600). The HHI takes into account both the number of firms and the relative sizes of the firms in a market. Hence, the index increases as the number of firms in the market decreases and as the disparity in size between those firms increases. The index approaches zero in a market with many firms of similar size and reaches its maximum of 10,000 points if there is a single firm in the market. Market regulators commonly employ the HHI to guide market policy. U.S. regulatory agencies generally consider markets in which the HHI is below 1500 to be unconcentrated, and markets with an index between 1500 and 2,500 points to be highly concentrated.[20] Further, the U.S. Federal Trade Commission presumes that transactions that increase the HHI by more than 200 points in highly concentrated markets are likely to enhance market power. In this paper, we create the Competition Index, defined as the inverse HHI, by subtracting the HHI from 10,000 (Boydstun, Bevan, and Thomas III, 2014). With this new measure of competition, a value of 8,500 or greater is competitive, a value between 7,500 and 8,500 is moderately competitive, and less than 7,500 is uncompetitive. Our summary statistics present the raw numbers, but our regression will use a standardized variable. From our descriptive table below, we can see that the passenger airline market is competitive.

[20] See U.S. Department of Justice & FTC, Horizontal Merger Guidelines §5.3 (2010).

2.4 Data

We use aviation accident and injury data from the National Transportation Safety Board (NTSB) and information on airlines, the number of pilots, demographic characteristics, and average wage from the Bureau of Transport Statistics (BTS) for the years 1995-2018. Serious incidents and accidents are rare occurrences that must be reported to the NTSB. Non-serious incidents do not have to be reported (AOPA, 2016).[21] After an accident or incident occurred, the NTSB sends a team of specialists to the accident site for investigation. Table C.11 shows descriptive statistics of the U.S. aviation industry. We have over 900 airline-year observations and airline-level statistics on pilots. The outcome variable of interest is the (log) average compensation per pilot, which is the mean of the pilot average wage, benefits, and pension at a given airline. This measure does not include other compensation or benefits such as, for example, traveling allowance, hotel quality, or whether or not one has to pay for their uniform. The main regressor of interest is the (log) number of pilots at an airline. The instrument is the accident count per airline in the previous year[22]. We split this sample into passenger airlines and cargo airlines. Our analysis is restricted to passenger airlines and contains 666 airline-year observations.

Data on pilot employment and compensation was collected from the Bureau of Transportation Statistics, Form 41, schedules P5.2, P6 and P10. Form P5.2 and P6 are quarterly information, while form P10 is yearly information, hence our unit of time is yearly. We control for inflation by making our compensation variable in dollars figure of the year 2018.[23] Since we do not have

[21] According to the NTSB definition, an accident is an occurrence associated with the operation of an aircraft that takes place between the time any person boards the aircraft and point in time when passengers disembark. Further, accidents are occurrences resulting death or serious injury of persons, or in which the aircraft receives substantial damage. Accidents are distinct from incidents, which are occurrences associated with the operation of an aircraft, which affects or could affect the safety of operations (CFR-830.2, n.d.).

[22] The airline can take a little while to adjust to the effects of the accidents

[23] Payroll data is provided by U.S. carriers for the Department of Transportation. P5.2, P6, and P10 data are submitted by large certificated air carriers; i.e. carriers operating at least one aircraft certified for 61 seats or more or a payload of 18,001 lbs. or more.

individual-level data, nor data on seniority, we are unable to control for seniority.[24] We also obtain net income of airlines from P5.2 as a control variable to capture the effect of profitability on wages.

2.5 Aviation Accidents as Instruments

Aviation accidents are rare but widely publicized events that loom large in the public imagination. When an airline experiences an accident, fewer people will buy tickets from this airline (Zotova, 2017b). We propose that accidents are an exogenous shock to consumer demand. We use this shock as an instrumental variable for the number of pilots employment by an airline in the following year. For this instrument to be valid, an accident has to affect demand for tickets from the affected airline. Further, the accident should not affect demand at competing airlines (those that did not experience an accident) or alter overall ticket demand. To further bolster this claim we estimate equation (5) for pilots at cargo airlines. We propose that pilots are well aware of the risk of an accident occurring and do not update their belief when an accident does occur at their airline. Further, we hold that pilots at passenger airlines and cargo airline pilots do not differ in that regard. If these propositions hold true, accidents at a cargo airline should not affect the number of pilots employed by an airline because cargo accidents do not result in a demand shock. As expected, we show that in the case of cargo airlines there is no relationship between accidents and the number of pilots (see Table 9). This supports the idea that accidents cause a demand shock that exogenously shifts the demand for pilots of passenger carriers. See Figure C.1 for accidents over time and Figure C.2 for the relationship between accidents and passenger volume.

How does an aviation accident affect pilot employment? The affected airline typically implements changes in its operation to improve safety or are forced to scale back their operations and hire fewer pilots. Airlines routinely evaluate what led to an accident, and consider whether the findings warrant further changes that could improve the safety of their aircrafts. Given the significance of human error, plausible adjustments would involve improving the working conditions of

[24]We could construct a seniority measure analogous to the one constructed by (Crémieux and Van Audenrode, 1996). However, many airlines are part of our sample for only a few years, as they do not always follow federal reporting requirements. Therefore, we are not confident that a valid seniority measure can be constructed from the available data.

pilots and hiring more staff to ensure safer operations (Billings and Reynard, 1984). In short, if an airline that experienced an accident wants to improve safety, it may hire additional pilots (rather than reduce employment). If the airline experiences significant financial strain as a result of the demand shock, it may have to cut labor costs. Airlines cannot adjust wages in the short-term because of the union-negotiated employment contracts.[25] However, bankruptcy protection provides airlines an opportunity to renegotiate union contracts, which is why we include an indicator for bankruptcy protection (Chaison, 2007). See Table C.6 for airline bankruptcies over time. Given the lack of alternatives, the primary way for airlines to cut labor costs is to adjust the rate at which they hire pilots (i.e. to replace retiring pilots).[26] This implies that it is likely that pilots' wages are affected by the demand shock (resulting from an accident) only through airlines' demand for labor.

Monopsonistic firms capture rents by setting wages below the competitive market level, thereby creating a labor shortage. We want to rule out that the observed labor shortage is caused by factors other than monopsony power. Are there any supply-side mechanisms that could have led to the observed pilot shortage? A plausible reason for an undersupply of pilots are the costs associated with obtaining the required training and licenses to work for a commercial airline. For example, in order to work for a commercial airline with regular scheduled flights, pilots need to obtain an Airline Transport Pilot License (ATPL). However, this licensure requirement does not appear to restrict the supply of pilots. Data from the FAA's U.S. Civil Airmen Statistics contains the number of pilots that have obtained the ATPL for the years 2005 to 2018, spanning most of our sample period.[27] In Table C.8 we show the number of pilots that have an active ATPL license and the number of pilots employed by commercial airlines as observed in our data. The number of pilots holding an ATPL exceeds the number of pilots employed at commercial airlines, making it unlikely that supply-side frictions are responsible for the observed pilot shortage.

[25]We exclude charter carriers from our analysis for two reasons. First, they operate differently from scheduled carriers. Specifically, contract structures for charter pilots differ from those of scheduled carriers. Second, charter carriers have low rates of unionization (45.6%) compared to scheduled carriers that are unionized at a rate of 85.17%, which would threaten the exclusion restriction.

[26]Training pilots and ensuring that they are current on an aircraft is expensive. Hence, the savings from not filling a vacant position are even greater than the nominal wage expenditures

[27]This can take anywhere from 750 flight hours for military pilots up to 1,500 flight hours for students in a flying school

2.6 Estimation Strategy

Our test of monopsony power focuses on estimating the residual labor supply curve facing each airline. Equation (4) is the firm-level wage equation as a function of the number of pilots.[28] Robust standard errors are clustered at the airline level.

$$log(wage_{it}) = \beta_0 + \mu\ log(pilots_{it}) + X_{it}^{'}\gamma + \alpha_i + \tau_t + \epsilon_{it} \tag{2.4}$$

where $wage_{it}$ is the average wage paid by an airline i in year t and $pilots_{it}$ is the amount of labor (number of pilots) that airline i employs in time t. The airline fixed effect is α_i, the year fixed effect is τ. The coefficient μ is the inverse of the labor supply elasticity facing the individual airline. In a competitive labor market the firm-level labor supply is infinite and we would observe $\mu = 0$. In contrast, if $\mu > 0$, the airline faces an upward sloping residual labor supply. $X_{it}^{'}$ is a vector of firm-level control variables that includes net income, and indicators for mergers, bankruptcies and pilot unions at an airline, as well as a market competition index.

In order to estimate Equation (4) using 2SLS we estimate the following first-stage. Equation (5) is the first stage equation of the number pilots on the number of accidents resulting from aviation incidents for airline i in year $t-1$. The airline fixed effect is α_i, the year fixed effect is τ. Robust standard errors are clustered at the airline level.

$$log(pilots_{it}) = \theta_0 + \theta_1\ accidents_{it-1} + X_{it}^{'}\delta + \alpha_i + \tau_t + \upsilon_{it} \tag{2.5}$$

In Table 2 we estimate equation (4) using OLS and 2SLS. The instrumental variable strategy relies on the assumption that the incidence of accidents affect pilot average wage only through the demand for air tickets and that pilot employment changes resulting from accidents are driven by the firms' response to the demand shock. We made this argument in section V.

[28]The outcome is the average wage by firm.

We are interested in how the labor supply elasticity varies with a measure of competition, through the inverse HHI. We ask, does employer monopsony power increase as the market becomes more competitive? We estimate this by adding the interaction between the number of pilots with Competition:

$$log(wage_{it}) = \beta_0 + \mu\, log(pilots_{it}) + \eta\, log(pilots_{it}) * Competition_t + X_{it}^{'}\gamma + \alpha_i + \tau_t + \epsilon_{it} \quad (2.6)$$

Our additional variable is the interaction between the endogenous variable, $log(pilots_{it})$, with an exogenous one, Competition. Hence, this interaction has an endogenous component that must be corrected during the first stage. The predicted value of log of pilots being exogenous can be replaced in the interaction to correct the endogeneity.

2.7 Results

We start by looking at the reduced form relationship of the log of the average wage on the log number of pilots. The results for equations (4) and (6) are in Table C.17.[29] Each regression includes airline and year fixed effects. We are interested in the labor supply elasticity, given by the inverse of the coefficient associated with the log number of pilots. The OLS coefficient of 0.0281, presented in column (1) implies a labor supply elasticity of 35.6, indicating minor monopsony power but is very noisily estimated. The issue, of course, is that both supply and demand may be moving simultaneously. As a result, we cannot interpret the OLS regression as a supply curve. To identify the residual labor supply elasticity facing a single airline, we use the lagged number of accidents to instrument for labor demand at the individual airline.

The second-stage coefficient of 0.400 in column (2) (significant at the 5% level) implies a residual labor supply elasticity of 2.5. Given the average wage of \$117,519, pilots face an exploitation gap of \$47,007 or 28.6%.[30] This estimate is large but not unreasonable (Manning, 2003). The finding indicates that airlines have substantial monopsony power in the labor market for pilots.

[29] First-stage results are presented in Table 12 of the appendix.

[30] The results are not meaningfully different if we exclude control variables from the regression.

Note that the variable *Competition*, which is the inverse HHI, has been standardized. The omitted dummy variable category for the type of airline is "Legacy carrier" referring to the major airlines. The coefficients for low-cost carriers (LCC), minor- and regional airlines are included in the table.

Column (4) presents the 2SLS results that allow us to measure the effect of market concentration on the labor supply elasticity.[31] To do so, we take the partial effect with respect to the log number of pilots and obtain 0.391-0.0239*Competition. At the mean value of the standardized Competition, 0, we obtain an inverse elasticity of 0.391, which corresponds to an elasticity of 2.56. This implies pilots are paid 28.11% below their marginal product. We perform a test of joint significance and a test on the partial effect evaluated at the mean and find that results are significant at 1%. An increase in Competition by 1 one standard deviation from the mean would cause an increase in elasticity by approximately 0.17 points, which corresponds to pilots being paid an additional 1.26%.

Our results from Table 4 show that as competition increases, wages increase slightly. When taking the partial effect with respect to Competition, we see that the turn around point for the log of quantity of pilots is at 13.47 , but the maximum value in our data is 9.52; the turn around point is never reached. The partial effect of Competition evaluated at the minimum, mean, and maximum values of log number of pilots yield values of 0.243, 0.165, and 0.094 respectively, implying that within the range of existing firm sizes, an increase in competition has a positive effect on wages. It would take a very large firm (more than twice the size of the largest current firm) to see wages fall as a result of an increase in competition.

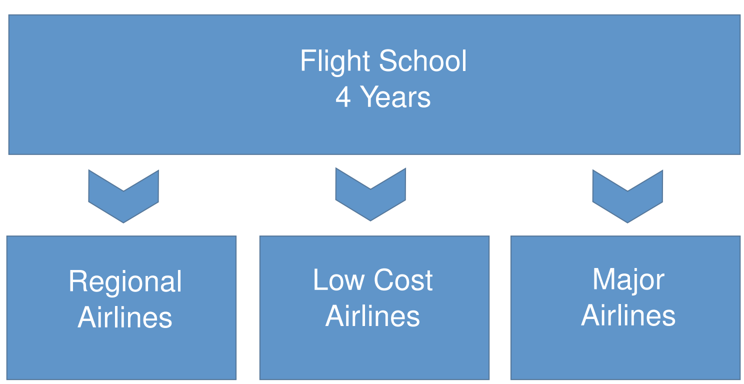
2.8 Policy Implications - Pilot Training Reform

According to our results, competition only slightly explains monopsony power. The source of monopsony power lies, at least partially, in the training structure and career flow path. In most of the world, pilots go through a different training program that allows them to enter a (final)

[31] Column (3) is the OLS regression that includes the interaction term.

job much earlier, which has wage ramifications. We propose that U.S. carriers adopt the similar approach. Specifically, many foreign companies have "Ab initio" programs that work as follows: potential pilots take a thorough interview exam,[32], if the potential pilot passes the exam, then he/she has the job guaranteed by the company contingent on successfully accomplishing the studies[33] Many carriers will finance the education by requiring that the pilot stays with the airline over a certain period of time. In most countries, such as in Europe, pilots can join the airline with 250 flight hours, which is what the United States had as a requirement for pilots to join a regional airline before PL 111-216 was implemented, which significantly increased flight hours with the intention of improving safety. Pilot Source Study conducted by Embry-Riddle has shown that there were no safety improvements linked to the PL 111-216. Therefore, we advise that pilots join airlines through an Ab initio program with 250 hours. An Ab initio program would allow pilots to enter a major airline directly after flight school is completed, allowing them to join the seniority list sooner, hence, to reach a higher earning for longer. Currently, the time they spend at flight schools providing instruction and the time they spend at a regional airline do not count towards the seniority. These years would then count towards seniority and earn higher wages. The training and career path would then look as follows:

Figure 2.3: Proposed Training and Career Path



[32]This exam varies by airline, but usually incorporates an aptitude test, a psychological exam, interview questions, and quantitative skills.

[33]Currently, only United Airlines has a contact with a flight academy to provide guidance in recruitment and training.

Training to become a pilot is risky. Pilots in training incur financial costs, yet only after they complete their training and apply for a job is the payoff revealed. One alternative is to screening applicants prior to training, which could allow airlines to attract better quality pilots. Entering the workforce earlier could also benefit pilots. Pilots in training would not have to spend time becoming instructors. Instead, they would enter a major or low-cost airline directly, much like U.S. military pilots (or as is done in many other countries). The productivity of pilots is fairly constant throughout their career. Entering sooner would enable pilots to enter the seniority list sooner. Once on the seniority list of a major carrier (or low cost carrier), pilots are paid a wage closer to their marginal product. Consequently, their total lifelong (average) earnings will higher; the wage gap will be smaller. Below is a wage simulation showing the current path taken by pilots[34] to the proposed path with direct entry. In this example, we use the Delta Airlines wages for the A320 and A350. The average wage in the current path in comparison to the proposed path is $154,467 and $180,314 respectively; the lifelong difference in earnings between the two options are $6,487,600 and $7,933,800, which is a difference of $1,446,200[35].

2.9 Conclusion

The U.S. airline industry, despite having seen a decrease in competitiveness over the past two decades, remains competitive according to the U.S. regulatory agencies. We show that airlines have a substantial ability to set wages, a common phenomenon for employers of highly specialized and skilled labor. Using aircraft accidents as an instrument for the labor demand we estimate the residual labor supply curve. We find that pilots are, on average, paid 28% below their marginal revenue product, a pareto inefficient outcome. We also find that a commonly used measure of market competition, the inverse HHI, is a poor predictor of monopsony power. Monopsony power is likely originating elsewhere. We make the case that the training structure and career trajectory introduce frictions that suppress wages. Time-intensive and expensive training programs do not

[34] Here pilots have to be instructors for a couple years, spend 7 years in a regional airline (at Sky West), and then go from being a FO on the A320, A350, then Captain on the A320, then A350.

[35] We do not include pension and benefits

select high ability candidates *ex-ante*, which means some graduates are not suitable to work as airline pilots.Policy changes after the Colgan Air crash in 2009 increased the training duration, delaying entry into the labor market.

In order to mitigate the efficiency loss, we propose implementing *ex-ante* training screening that will make pilots eligible for a shorter training program (similar to *Ab initio* programs or military training). Providing student loans could relax financing constraints, which could attract more applications, and allow for selection of higher ability candidates. Graduating pilots would be qualified to start their career at higher paying low-cost or legacy carrier. Simulations show a lifelong earning difference of $1,446,200. While training and hiring frictions may not be the only source of monopsony power, it can be addressed by policy maker by implementing pilot training reform.

Chapter 3

Improved Likelihood-Based Inference for Treatment Effects in Small Samples: Application to Aviation Data

3.1 Introduction

Small samples complicate causal inference because of sampling error, lack of power and distributional assumptions. We apply recent likelihood theory to derive p-values that more accurately assess the treatment effect parameter for the impact evaluation in the regression analysis context with normal or general non-normal error distributions. For this, we use the conditional likelihood-based method developed in (Fraser and Reid, 1995), which has $O(n^{-3/2})$ distributional accuracy and uses conditional techniques to assess the departure of data from a hypothesized parameter value. Within this intrinsic conditional framework the likelihood methods invoke distributional techniques closely related to the saddle-point approach. As such, they have been found to give exceptionally high accuracy even in the case of minimal sample size. A particular merit of this approach is that it provides substantial improvements on the usual methods (e.g. likelihood ratio, Wald, bootstrap tests) and is superior in terms of central coverage and error rate even for very small sample sizes. These results have particular appeal to applied researchers dealing with impact evaluation models when the sample size is very small. The procedure is applied to a real data set from aviation industry to reassess the impact accidents on airfares, which could have ramifications for airlines that want to hedge against losses.

The approach proposed in this paper is based on recent developments in analytical approximations for parametric inference in small samples, initiated by Fisher (1934) but largely overlooked until new developments were stimulated by Efron and Hinkley (1978) and (Barndorff-Nielsen and Cox, 1979). A flood of subsequent work is summarized in the books of (Cox and Barndorff-Nielsen, 1994), (Pace and Salvan, 1997), and(Severini, 2000). The efforts of many researchers, particularly (Barndorff-Nielsen, 1983; Barndorff-Nielsen, 1986) , Fraser (1990), (Fraser, Reid, and Wu, 1999), have led to an elegant theory of near-exact inference based on small samples from parametric models. Its theoretical basis is the saddle-point and related approximation discussed by Daniels (1954, 1987), and further developments have been well described by Reid (1988, 1995, 2003). These methods are highly accurate in many situations, and can be conducted regardless of the sample size in order to determine the extent to which first-order methods can be relied upon.

The two main contributions of this paper are as follows. First, higher-order likelihood theory is used to obtain highly accurate p-values for treatment effect in impact evaluation models. Second, an empirical application is given in which the impact of a government protectionist training policy is examined using data from aviation industry with a limited number of participants.

3.2 Background

Let $Y_1, \ldots, Y_n$ be independently and identically distributed from a parametric model with log-likelihood function given by $l(\theta; y)$. Assume the full parameter $\theta = (\psi, \lambda')'$ is p dimensional. The variable ψ represents the scalar component interest parameter and the vector λ is the $p-1$ dimensional nuisance parameter. Maximization of this function with respect to θ yields the maximum likelihood estimate $\hat{\theta} = (\hat{\psi}, \hat{\lambda}')'$. The constrained maximum likelihood estimate denoted by $\hat{\theta}_\psi = (\psi, \hat{\lambda}'_\psi)'$ is obtained by maximizing the log-likelihood function over λ for a fixed value of ψ. Based on the log-likelihood function, two familiar statistics can be used to compute confidence intervals for ψ. The Wald statistic (q)

$$q = (\hat{\psi} - \psi)\{j^{\psi\psi}(\hat{\theta})\}^{-1/2} \tag{3.1}$$

and the signed log-likelihood ratio statistic (r)

$$r = sgn(\hat{\psi} - \psi)[2\{l(\hat{\theta}) - l(\hat{\theta}_\psi)\}]^{1/2}, \tag{3.2}$$

where $j^{\psi\psi}(\hat{\theta})$ is represented in the estimated asymptotic variance of $\hat{\theta}$:

$$j^{\theta\theta'}(\hat{\theta}) = \{j_{\theta\theta'}(\hat{\theta})\}^{-1} = \begin{bmatrix} j^{\psi\psi}(\hat{\theta}) & j^{\psi\lambda'}(\hat{\theta}) \\ j^{\psi\lambda'}(\hat{\theta}) & j^{\lambda\lambda'}(\hat{\theta}) \end{bmatrix}.$$

The matrix $j_{\theta\theta'}(\theta)$ is the information matrix which contains the second derivatives of the log-likelihood function:

$$j_{\theta\theta'}(\theta) = \begin{bmatrix} -l_{\psi\psi}(\theta) & -l_{\psi\lambda'}(\theta) \\ -l_{\psi\lambda'}(\theta) & -l_{\lambda\lambda'}(\theta) \end{bmatrix} = \begin{bmatrix} j_{\psi\psi}(\theta) & j_{\psi\lambda'}(\theta) \\ j_{\psi\lambda'}(\theta) & j_{\lambda\lambda'}(\theta) \end{bmatrix}.$$

The statistics given in (3.1) and (3.2) are asymptotically distributed as the standard normal with an $O(n^{-1/2})$ rate of convergence. These approximations are thus accordingly known as first-order approximations. Tail probabilities for inference on ψ can be approximated using either of these statistics with the cumulative standard normal distribution function $\Phi(\cdot)$, i.e. $\Phi(q)$ and $\Phi(r)$. These first-order methods can however be extremely inaccurate when the sample size is small or when the original distribution not normal.

For higher-order inference on the parameter ψ, (Barndorff-Nielsen, 1991) derived a third-order tail probability approximations using saddlepoint methods:

$$r^* = r - \frac{1}{r}\log\left(\frac{r}{Q}\right) \tag{3.3}$$

The statistic r^* is known as the modified signed log-likelihood ratio statistic and the statistic r is the signed log-likelihood ratio statistic defined in (3.2). The statistic Q is a standardized maximum likelihood departure whose expression depends on the type of information available. Approximation (3.3)has an $O(n^{-3/2})$ rate of convergence to the standard normal distribution and is thus referred to as third-order approximation.

For exponential family models, several definitions for Q exist, see for example, Barndorff-Nielsen (1991), Pierce and Peters (1992), Fraser and Reid (1995), and Jensen (1995). The derivation of Q given by Fraser and Reid (1995) is used in this paper. They use tangent exponential models to derive a highly accurate approximation to the p-value for testing a scalar interest parameter. Obtaining Q involves two main components. The first component requires a reduction of dimension by approximate ancillarity. This step reduces the dimension of the variable to the dimension of the full parameter. The second component requires a further reduction of dimension from the dimension of the parameter to the dimension of the scalar interest parameter. These two components are achieved through two key reparameterizations: from the parameter θ to a new parameter $\varphi(\theta)$, and from the parameter $\varphi(\theta)$ to a new parameter $\chi(\theta)$.

The ancillary directions V can be obtained as follows:

$$V = \left.\frac{\partial y}{\partial \theta'}\right|_{\hat{\theta}} = -\left.\left(\frac{\partial z}{\partial y'}\right)^{-1}\left(\frac{\partial z}{\partial \theta'}\right)\right|_{\hat{\theta}}. \tag{3.4}$$

The variable z represents a pivotal quantity of the model whose distribution is independent of θ.

These ancillary directions are used to calculate the locally defined canonical parameter, φ:

$$\varphi'(\theta) = \left[\frac{\partial l(\theta; y)}{\partial y}\right] V. \tag{3.5}$$

Given this new reparameterization, the original parameter of interest must thus be recalibrated. This recalibration results in the new parameter χ:

$$\chi(\theta) = \frac{\psi_{\varphi'}(\hat{\theta}_\psi)}{\left|\psi_{\varphi'}(\hat{\theta}_\psi)\right|}\varphi(\theta), \tag{3.6}$$

where $\psi_{\varphi'}(\theta) = \partial\psi(\theta)/\partial\varphi' = (\partial\psi(\theta)/\partial\theta')(\partial\varphi(\theta)/\partial\theta')^{-1}$. The modified maximum likelihood departure is then constructed in the φ space. The expression for Q is given by

$$Q = sgn(\hat{\psi} - \psi)|\chi(\hat{\theta}) - \chi(\hat{\theta}_\psi)|\left\{\frac{|\hat{\jmath}_{\varphi\varphi'}(\hat{\theta})|}{|\hat{\jmath}_{(\lambda\lambda')}(\hat{\theta}_\psi)|}\right\}^{1/2}, \tag{3.7}$$

where $\hat{\jmath}_{\varphi\varphi'}$ and $\hat{\jmath}_{(\lambda\lambda')}$ are the observed information matrix evaluated at $\hat{\theta}$ and observed nuisance information matrix evaluated at $\hat{\theta}_\psi$, respectively, calculated in terms of the new $\varphi(\theta)$ reparameterization. The determinants can be computed as follows:

$$\begin{aligned} |\hat{\jmath}_{\varphi\varphi'}(\hat{\theta})| &= |\hat{\jmath}_{\theta\theta'}(\hat{\theta})||\varphi_{\theta'}(\hat{\theta})|^{-2} \\ |\hat{\jmath}_{(\lambda\lambda')}(\hat{\theta}_\psi)| &= |\hat{\jmath}_{\lambda\lambda'}(\hat{\theta}_\psi)||\varphi'_{\lambda}(\hat{\theta}_\psi)\varphi_{\lambda'}(\hat{\theta}_\psi)|^{-1}. \end{aligned} \tag{3.8}$$

The interested reader is directed to Fraser and Reid (1995) and Fraser, Reid and Wu (1999) for the mathematical details of the methodology. Given the overall objective is to obtain highly accurate confidence intervals for the interest parameter ψ, we can use Q and r in formulas (3.3) to obtain a $(1-\alpha)100\%$ confidence interval for ψ as follows.

$$CI_{\psi} = \left\{\psi : |r^{*}(\psi)| < z_{\alpha/2}\right\}, \tag{3.9}$$

where $z_{\alpha/2}$ is the $(1-\alpha/2)100^{th}$ percentile of the standard normal distribution.

3.3 Accurate Inference for the Treatment Effect Parameter

Consider the following specification of the usual treatment effects model. The outcome variable, y_i, is related to the k–vector of exogenous covariates (containing the intercept), x_i, and the treatment indicator, D_i (that takes the value 1 if unit i is treated, and 0 otherwise), by

$$y_i = \psi D_i + x_i'\beta + \epsilon_i, \quad \epsilon_i | D_i, x_i \sim N(0,\, \sigma^2) \tag{3.10}$$

where ψ is the scalar parameter capturing the treatment effect of interest, β is a parameter vector of size $k \times 1$, and ϵ_i is a normally distributed disturbance term with variance σ^2.

We are interested in determining whether there is a causal relationship between the treatment status D and the outcome y. We are therefore focusing in testing the the significance of the treatment effect parameter ψ, that is the null hypothesis is, $\psi = 0$, against the alternative hypothesis $\psi \neq 0$. Our framework however, allows us to test for a general hypothesis of the form $H_0 :\ \psi = \psi_0$ against the alternative $H_1 :\ \psi \neq \psi_0$, for some finite value $\psi_0 \in \mathbb{R}$.

Implicit to our model specification is the assumption that the treatment status is exogenous. This assumption may be restrictive in many empirical applications where participation to the program in voluntary and hence endogenous to the outcome. However in many cases such as in experimental and quasi-experimental studies, this is fairly reasonable. The application we discussed is one where a policy has been implemented by the government, and can be thought of as being fairly exogenous to the outcome considered at the airline company level, as we discussed in the application section. Since our focus is in deriving a method for inference when the size of the sample is the main issue, we abstract from the dependence of D_i on ϵ_i and/or some auxiliary covariates. Our procedure can however be easily extended to accommodate these cases as well, as we discuss later.

For a random sample of size n, equation (3.10) can be re-written in the matrix form as

$$y = \psi D + X\beta + \varepsilon, \tag{3.11}$$

where $y = [y_1, \ldots, y_n]'$, $X = [x_1, \ldots, x_n]'$, $D = [D_1, \ldots, D_n]'$, and $\varepsilon = [\varepsilon_1, \ldots, \varepsilon_n]'$.

For the parameter vector $\theta = (\psi,\, \lambda')' = (\psi,\, \beta',\, \sigma^2)'$, the probability density function of ε is given by

$$f(y;\theta) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left[-\frac{1}{2\sigma^2}\left(y - \psi D - X\beta\right)'\left(y - \psi D - X\beta\right)\right]$$

The notation here follows the notation in the previous section, where $\lambda = (\beta',\, \sigma^2)'$ corresponds to the nuisance parameter vector of the model. The log-likelihood function (with the constant dropped) is then given by

$$l(\theta; y) = -\frac{n}{2}\log\sigma^2 - \frac{1}{2\sigma^2}\left(y - \psi D - X\beta\right)'\left(y - \psi D - X\beta\right) \tag{3.12}$$

The overall maximum likelihood estimate (MLE) of θ, denoted as $\widehat{\theta}$, is obtained by simultaneously solving the first-order conditions $l_\theta(\hat{\theta}; y) = 0$.

$$\begin{aligned}
l_\psi(\hat{\theta}; y) &= \frac{1}{\hat{\sigma}^2} D'\left(y - \hat{\psi}D - X\hat{\beta}\right) = 0 \\
l_\beta(\hat{\theta}; y) &= \frac{1}{\hat{\sigma}^2} X'\left(y - \hat{\psi}D - X\hat{\beta}\right) = 0 \\
l_{\sigma^2}(\hat{\theta}; y) &= -\frac{n}{2\hat{\sigma}^2} + \frac{1}{2\hat{\sigma}^4}\left(y - \hat{\psi}D - X\hat{\beta}\right)'\left(y - \hat{\psi}D - X\hat{\beta}\right) = 0
\end{aligned} \tag{3.13}$$

By solving this system, it is easy to obtain the following result:

$$\hat{\psi} = \left(D' M_X D\right)^{-1} D' M_X y;$$
$$\hat{\beta} = \left(X' M_D X\right)^{-1} X' M_D y;$$
$$\hat{\sigma}^2 = \frac{1}{n}\left(y - \hat{\psi} D - X\hat{\beta}\right)'\left(y - \hat{\psi} D - X\hat{\beta}\right)$$

where M_Z is the "residual maker" from the matrix Z, defined by $M_Z = I - Z'(Z'Z)^{-1}Z$.

Given this information about the likelihood function and the overall maximum likelihood estimate the information matrix $j_{\theta\theta}(\hat{\theta})$ can then be constructed using the second derivatives of the log-likelihood function given by:

$$\begin{aligned}
l_{\psi\psi}(\theta; y) &= -\frac{1}{\sigma^2} D' D \\
l_{\psi\beta}(\theta; y) &= -\frac{1}{\sigma^2} D' X \\
l_{\psi\sigma^2}(\theta; y) &= -\frac{1}{\sigma^4} D' \left(y - \psi D - X\beta\right) \\
l_{\beta\beta}(\theta; y) &= -\frac{1}{\sigma^2} X' X \\
l_{\beta\sigma^2}(\theta; y) &= -\frac{1}{\sigma^4} X' \left(y - \psi D - X\beta\right) \\
l_{\sigma^2\sigma^2}(\theta; y) &= \frac{n}{2\sigma^4} - \frac{1}{\sigma^6}\left(y - \psi D - X\beta\right)'\left(y - \psi D - X\beta\right)
\end{aligned} \tag{3.14}$$

Hence the observed information matrix is given by

$$j_{\theta\theta}(\hat{\theta}) = \frac{1}{\hat{\sigma}^2}\begin{pmatrix} D'D & D'X & 0 \\ X'D & X'X & \mathbf{0} \\ 0 & \mathbf{0} & \frac{n}{2\hat{\sigma}^2} \end{pmatrix}.$$

The most commonly used statistic for testing the value of ψ is the student t-test statistic defined by:

$$t = \frac{\hat{\psi} - \psi}{s_{\hat{\psi}}} = \sqrt{\frac{n-k}{n}}\, q \tag{3.15}$$

where $s_{\hat{\psi}}$ is the standard error of $\hat{\psi}$ from ordinary least square estimation (OLS) and q is the statistic given in (3.1). Clearly, t is a degree-of-freedom adjustment of the statistic q.

The constrained maximum likelihood estimate of θ, denoted as $\widehat{\theta_\psi}$, is obtained by simultaneously solving the first-order conditions $l_\theta(\hat{\theta}_\psi; y) = 0$.

$$
\begin{aligned}
l_\beta(\hat{\theta}; y) &= \frac{1}{\hat{\sigma}_\psi^2} X' \left(y - \hat{\psi} D - X\hat{\beta}_\psi \right) = 0 \\
l_{\sigma^2}(\hat{\theta}; y) &= -\frac{n}{2\hat{\sigma}_\psi^2} + \frac{1}{2\hat{\sigma}_\psi^4} \left(y - \hat{\psi} D - X\hat{\beta}_\psi \right)' \left(y - \hat{\psi} D - X\hat{\beta}_\psi \right) = 0
\end{aligned}
\tag{3.16}
$$

Similarly, we can construct the constrained information matrix $j_{\lambda\lambda'}(\theta)$ using the the following second-order derivatives:

$$
\begin{aligned}
l_{\beta\beta}(\hat{\theta}_\psi; y) &= -\frac{1}{\hat{\sigma}_\psi^2} X'X \\
l_{\beta\sigma^2}(\hat{\theta}_\psi; y) &= -\frac{1}{\hat{\sigma}_\psi^4} X' \left(y - \psi D - X\hat{\beta}_\psi \right) \\
l_{\sigma^2\sigma^2}(\hat{\theta}_\psi; y) &= \frac{n}{2\hat{\sigma}_\psi^4} - \frac{1}{\hat{\sigma}_\psi^6} \left(y - \psi D - X\hat{\beta}_\psi \right)' \left(y - \psi D - X\hat{\beta}_\psi \right)
\end{aligned}
\tag{3.17}
$$

Which yields the following observed constrained information matrix:

$$
j_{\lambda\lambda'}(\hat{\theta}_\psi) = \frac{1}{\hat{\sigma}_\psi^2} \begin{pmatrix} X'X & \mathbf{0} \\ \mathbf{0} & \dfrac{n}{2\hat{\sigma}_\psi^2} \end{pmatrix}.
$$

For the proposed third-order inference approach, two components are required to obtain the new locally defined canonical parameter $\varphi(\theta)$ given by (3.5). The first is the sample space gradient evaluated at the data, which is the derivative of (3.12) with respect to y given by

$$
\frac{\partial l(\theta; y)}{\partial y} = -\frac{1}{\sigma^2} \left(y - \psi D - X\beta \right)
$$

The second is the ancillary direction V which can be obtained from the full-dimensional pivotal quantity, $z(y; \theta)$, defined here as the vector of independent standard normal deviates given by:

$$z(y;\theta) = \frac{1}{\sigma}\left(y - \psi D - X\beta\right)$$

Following (3.4) the ancillary direction array is then obtained as follows

$$V = \left(\frac{\partial z}{\partial y'}\right)^{-1}\left(\frac{\partial z}{\partial \theta'}\right)\Bigg|_{\hat{\theta}} = \left[-D,\ -X,\ -\frac{y - \hat{\psi}D - X\hat{\beta}}{2\hat{\sigma}^2}\right]$$

Using the above results, the new locally defined canonical parameter is obtained as

$$\begin{aligned}
\varphi(\theta)' &= \frac{\partial l(\theta;y)}{\partial y'}V = [\varphi_1(\theta),\ \ \varphi_2(\theta),\ \ \varphi_3(\theta)] \\
&= \left[\frac{1}{\sigma^2}\left(y - \psi D - X\beta\right)' D,\ \frac{1}{\sigma^2}\left(y - \psi D - X\beta\right)' X,\right. \\
&\qquad \left.\frac{1}{\sigma^2 2\hat{\sigma}^2}\left(y - \psi D - X\beta\right)'(y - \hat{\psi}D - X\hat{\beta})\right]
\end{aligned}$$

where $\varphi_1(\theta)$, $\varphi_2(\theta)$ and $\varphi_3(\theta)$ are respectively, a 1×1, $1\times k$ and 1×1 parameter vectors.

The above expression therefore shows the dimension reduction from n, the dimension of the variable y, to $k+2$, the dimension of the model parameter vector θ.

Obtaining further reduction to the dimension of the interest parameter ψ, requires $\chi(\theta)$. Following (3.6), the scalar parameter $\chi(\theta)$ involves both $\varphi(\theta)$ and the constrained maximum likelihood estimate $\hat{\theta}_\psi$. The latter can be obtained by maximizing the likelihood function (3.12) with respect to $\lambda = (\beta', \sigma^2)'$, while holding ψ fixed at its hypthesized value. This yields a vector $\hat{\theta}_\psi = (\psi,\ \hat{\lambda}'_\psi)' = (\psi,\ \hat{\beta}'_\psi,\ \hat{\sigma}^2_\psi)'$ defined by

$$\hat{\beta}_\psi = \left(X'X\right)^{-1} X'\left(y - \psi D\right); \qquad \hat{\sigma}^2_\psi = \frac{1}{n}\left(y - \psi D - X\hat{\beta}_\psi\right)'\left(y - \psi D - X\hat{\beta}_\psi\right)$$

where ψ is the hypthesized treatment effect to be tested. The other required component of $\chi(\theta)$ is the quantity $\psi_{\varphi'}(\theta) = \frac{\partial\psi(\theta)}{\partial\theta'}\left[\frac{\partial\varphi(\theta)}{\partial\theta'}\right]^{-1}$ which is evaluated at the constrained MLE $\hat{\theta}_\psi$. In this expression, the first term is given by

$$\frac{\partial\psi(\theta)}{\partial\theta'} = \left[\frac{\partial\psi(\theta)}{\partial\psi}; \frac{\partial\psi(\theta)}{\partial\beta'}; \frac{\partial\psi(\theta)}{\partial\sigma^2}\right] = [1; 0_{1\times k}; 0],$$

whereas the second term is given by

$$\varphi_{\theta'}(\hat{\theta}_\psi) = \left.\frac{\partial \varphi(\theta)}{\partial \theta'}\right|_{\hat{\theta}_\psi} = \left.\begin{pmatrix} \frac{\partial \varphi_1(\theta)}{\partial \psi} & \frac{\partial \varphi_1(\theta)}{\partial \beta'} & \frac{\partial \varphi_1(\theta)}{\partial \sigma^2} \\ \frac{\partial \varphi_2(\theta)}{\partial \psi} & \frac{\partial \varphi_2(\theta)}{\partial \beta'} & \frac{\partial \varphi_2(\theta)}{\partial \sigma^2} \\ \frac{\partial \varphi_3(\theta)}{\partial \psi} & \frac{\partial \varphi_3(\theta)}{\partial \beta'} & \frac{\partial \varphi_3(\theta)}{\partial \sigma^2} \end{pmatrix}\right|_{\hat{\theta}_\psi} = -\frac{1}{\hat{\sigma}^2_\psi}\begin{pmatrix} D'D & X'D & \frac{e'_\psi D}{\hat{\sigma}^2_\psi} \\ D'X & X'X & \mathbf{0} \\ \frac{D'e}{2\hat{\sigma}^2} & \mathbf{0} & \frac{1}{2\hat{\sigma}^2\hat{\sigma}^2_\psi}e'_\psi e \end{pmatrix},$$

where $e_\psi = y - \psi D - X\hat{\beta}_\psi$, and $e = y - \hat{\psi}D - X\hat{\beta}$. Furthermore,

$$\varphi_{\theta'}(\hat{\theta}) = \left.\frac{\partial \varphi(\theta)}{\partial \theta'}\right|_{\hat{\theta}} = \left.\begin{pmatrix} \frac{\partial \varphi_1(\theta)}{\partial \psi} & \frac{\partial \varphi_1(\theta)}{\partial \beta'} & \frac{\partial \varphi_1(\theta)}{\partial \sigma^2} \\ \frac{\partial \varphi_2(\theta)}{\partial \psi} & \frac{\partial \varphi_2(\theta)}{\partial \beta'} & \frac{\partial \varphi_2(\theta)}{\partial \sigma^2} \\ \frac{\partial \varphi_3(\theta)}{\partial \psi} & \frac{\partial \varphi_3(\theta)}{\partial \beta'} & \frac{\partial \varphi_3(\theta)}{\partial \sigma^2} \end{pmatrix}\right|_{\hat{\theta}} = -\frac{1}{\hat{\sigma}^2}\begin{pmatrix} D'D & X'D & \frac{e'D}{\hat{\sigma}^2} \\ D'X & X'X & \mathbf{0} \\ \frac{D'e}{2\hat{\sigma}^2} & \mathbf{0} & \frac{1}{2\hat{\sigma}^4}e'e \end{pmatrix},$$

$$\varphi_{\lambda'}(\hat{\theta}_\psi) = \left.\frac{\partial \varphi(\theta)}{\partial \lambda'}\right|_{\hat{\theta}_\psi} = \left.\begin{pmatrix} \frac{\partial \varphi_1(\theta)}{\partial \beta'} & \frac{\partial \varphi_1(\theta)}{\partial \sigma^2} \\ \frac{\partial \varphi_2(\theta)}{\partial \beta'} & \frac{\partial \varphi_2(\theta)}{\partial \sigma^2} \\ \frac{\partial \varphi_3(\theta)}{\partial \beta'} & \frac{\partial \varphi_3(\theta)}{\partial \sigma^2} \end{pmatrix}\right|_{\hat{\theta}_\psi} = -\frac{1}{\hat{\sigma}^2_\psi}\begin{pmatrix} X'D & \frac{e'_\psi D}{\hat{\sigma}^2_\psi} \\ X'X & \mathbf{0} \\ \mathbf{0} & \frac{1}{2\hat{\sigma}^2\hat{\sigma}^2_\psi}e'_\psi e \end{pmatrix},$$

With the calculation of the determinants given in (3.8), the departure measure, Q, can then be calculated from (3.7). Third-order inference for the treatment effect ψ can then be obtained from plugging the above quantities into either (3.3) or by computing the associate p-values.

3.4 Application to Aviation Data

In the simulation section, we have confirmed the theoretical accuracy of our third-order approximation model for the treatment effect. In this section, we present an empirical example to illustrate the usefulness of our method. Applying our approximation for p-values to a regression framework, we test the effect of airline accidents, our exogenous treatment, on airfares. Our accident data comes from the National Safety Transportation Board. Accidents is a dummy variable equal to one if the airline had an accident during the year 1996 or during the last quarter of 1995 and 0 otherwise[1]. Our control variables are computed using data from the Bureau of Transportation Statistics. We also control for the average city population size of each airline's destination endpoints (U.S. Census data). The unit of observation is an airline, with a sample size of 30. Airfare data is obtained from the U.S. Department of Transportation's DB1B database, which is a 10 percent quarterly sample of all domestic airline tickets. Yearly averages of airfares have been computed. This application has been inspired by (Gerardi and Shapiro, 2009) and (Zotova, 2017a). The following regression model is employed:

$$log(airfares)_i = \beta_0 + \psi accident_i + \beta X_i + \epsilon_i \tag{3.18}$$

where $log(airfares)$ is the log of the average airfare price, $accident$ is the treatment variable for each airline and our control variables are the $mean\ population$ of the endpoint cities, the number of $routes$ each airline operates, the average $market\ share$ for airline on the routes that it serves, the quantity of payload, that is of cargo transported in pounds, and the average $distance$ of its flights. The variables $mean\ population$, $market\ share$, $routes$, and $distance$ are yearly averages by airline, the variable $payload$ is the total payload transported by airline. Specifically, to compute the $market\ share$ variable, we calculate each airline's market share per route, and then take the average across routes.

Larger cities cause higher demand for the route, which should increase fares. Since more densely populated cities simultaneously attract more competition to deserve the demand, the effect of the market forces can push prices down. For a fixed distance, flights between two large cities are cheaper than flights between a large and small city, which is cheaper than a flight between two small cities (such as between two remote destinations). As in airline becomes larger, it serves more routes, which is positively correlated with greater market share (correlation 0.373). With more routes, the airline can serve more destinations, many of which are less populated (even remote) that can be more expensive. Similarly, an airline's ability to set ticket prices is expected to rise with its market share on a particular route. Hence, we expect a positive sign for the coefficient.

[1] We code the treatment to be equal to one if the airline had an accident in the previous quarter of the year examined since Zotova (2017) has demonstrated that the effects of accidents on airfares last for approximately a quarter.

Airlines can carry payload in the "belly"[2] of the aircraft, also known as cargo.[3] Cargo also generates revenue, which means greater payload capacity reduces pressure to generate revenue on seats sold to passengers. Therefore, carrying more payload allows airlines to be more competitive on airfares. Hence, we expect a negative sign. The variable distance is added to capture the effect of the variable cost. To operate a flight, airlines need to pay for wages, fuel, maintenance, traffic routes (airlines have to obtain traffic rights to fly on a route and pay per mile flown) etc. As the distance becomes larger, carriers may need a larger plane that costs more to land[4]. Hence, distance should have a positive effect on prices. However, larger aircrafts also provide economies of scale, which can have a negative impact on fares.

Table 2 below provides descriptive statistics of our data. Table 3 provides reports results from a naive regression. Table 4 presents the estimation for the computed maximum likelihood estimators. In both tables, to provide more interpretable results, the variables $mean\ population$, $payload$ have been divided by 100,000, $departures$ been divided by 10,000, $routes$, $distance$ has been divided by 1000, and $marketshare$ have been divided by 100. We can see that the estimators used to generate the results in Table 3 and 4 give similar values, however, the maximum likelihood estimator provides smaller standard errors. The MLE estimates are then used to build confidence intervals for ψ as described in the previous sections. Table 5 reports the 95% confidence intervals for ψ obtained using the statistics r, Q, t, and r^*. The resulting confidence intervals display variation that could lead to different inferences about ψ. We can see that the confidence intervals vary in both width and range. These results show that r^* provides greater precision of our parameter estimate and captures a different range of estimates for ψ. These four statistics can lead to different decisions in terms of inference. Methods Q, t, and r contain points of disagreement with r^*, such as 0.42, hence a parameter estimate of 0.43 would be be significant in other methods but insignificant in ours. In all confidence intervals, the value zero is included, implying that accidents do not have

[2]The belly of an aircraft is located in the bottom of the plane where luggage's and cargo are stored.

[3]Cargo includes mail, boxes, containers, or animals, which can be transported as a third party for other airlines.

[4]Landing costs are priced according to the empty weight of an aircraft

an effect on airfares on a yearly level. This result is consistent with Zotova (2017) who found in her research on the impact of a crash on airfares that prices are only affect for a few months and dissipate soon after, making the impact on a yearly level minimal.

3.5 Conclusion

This paper employs a third-order likelihood theory to derive more trustworthy p-values for testing the significance of an exogenous treatment variable in cross-sectional linear regressions for small and medium sample settings. We illustrate the implementation of the proposed method using a regression of airfares on accidents and control variables. Our results show that our method captures points of disagreement, which stresses the advantages of this approach.

Table 3.1: Summary Statistics

Variable	Variable Definition	Min	Max	Mean	SD
Airfares	Average airfare (in dollars)	38.46	211.563	120.65	46.34
Accident	Dummy variable (=1 for accident)	0	1	0.467	0.507
Mean Population	Average end city population size at destination endpoints (in thousands)	225.563	11,100	3,987.2	2,227.3
Routes	Total number of routes per airline	12.645	1261.826	311.647	382.462
Market Share	Average market share on routes deserved	25.974	87.019	58.885	16.148
Payload	Total payload quantity (in thousands)	230.900	4572.794	1474.188	1035.808
Distance	Average distance of flights performed	143.86	2,938.414	760.186	534.569
Observations	30				

Table 3.2: Results for the naive regression

Parameter	Estimates	Standard Error
Accident	-0.1843	0.142
Mean Population (divided by 100,000)	0.00495	0.004
Routes (divided by 1000)	0.0963	0.049
Market Share (divided by 100)	0.326	0.399
Payload (divided by 100,000)	-0.0146	0.0058
Distance (divided by 1000)	-0.0415	0.0145
Observations	30	

Table 3.3: Results for the maximum likelihood estimation

Parameter	Estimates	Standard Error
Accident	-0.1843	0.1216
Mean Population (divided by 100,000)	0.00495	0.003
Routes (divided by 1000)	0.0963	0.0423
Market Share (divided by 100)	0.326	0.3416
Payload (divided by 100,000)	-0.0146	0.0049
Distance (divided by 1000)	-0.0415	0.0125
Observations	30	

Table 3.4: Results for 95% CI for ψ

Methodology	95% CI for ψ
r	(-0.06, 0.42)
Q	(-0.05 , 0.42)
t	(-0.05 , 0.43)
r*	(-0.1 , 0.47)

Appendices

Appendix A. Appendix for Chapter 1

Figure A.1: CDF of Injury Count

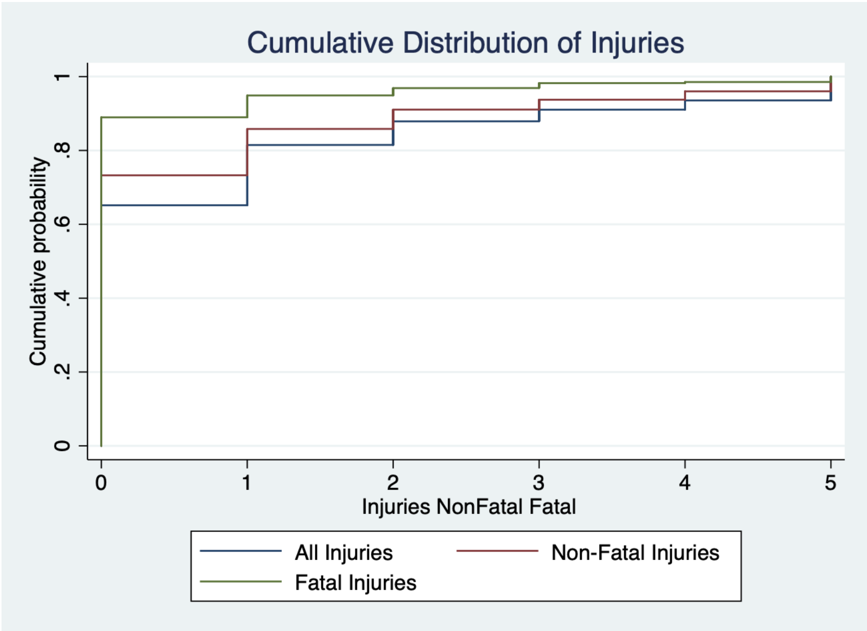


Table A.1: Negative Binomial Estimation Results Inverse CR8

VARIABLES	(1) Injury Count	(2) Injury Count	(3) Injury Count
Captain Experience	-0.0807**	-0.0771**	-0.0774**
	(0.0338)	(0.0373)	(0.0361)
Last 90 Days	1.893	-0.383**	1.370
	(1.227)	(0.180)	(1.149)
Age	0.0932	0.328	0.345
	(0.0730)	(0.208)	(0.219)
Age x L90D	-0.0503*		-0.0380
	(0.0283)		(0.0257)
1em] AGE Squared		-0.00357	-0.00302
		(0.00231)	(0.00222)
Aircraft Weight	0.0328**	0.0360**	0.0350**
	(0.0159)	(0.0170)	(0.0174)
Aircraft Age	-0.0601	-0.0642	-0.0613
	(0.101)	(0.0994)	(0.0996)
Dark Flying Conditions	0.861***	0.800***	0.874***
	(0.286)	(0.301)	(0.285)
Favorable Flying Conditions	0.278	0.227	0.221
	(0.367)	(0.405)	(0.377)
Inverse CR8	0.388**	0.372**	0.372**
	(0.174)	(0.176)	(0.173)
Observations	850	850	850
Pseudo R-squared	0.1634	0.1642	0.1653

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Variables explained: Captain Experience is the total experience of the captain in thousands of hours. Last 90 Days is the total number of (hundred) hours the captain has flown the past 90 days. Age is the age of the captain. Aircraft Weight is the aircraft weight in thousands of pounds. Aircraft Age is the aircraft age in thousand of flight hours. Dark Flying Conditions is a dummy variable equal to 1 if the flight is operated under dark flying conditions, and 0 otherwise. Favorable Flying Conditions is a dummy variable equal to 1 if the flight is operated under visual flight conditions, and 0 otherwise. Inverse CR8 is the inverse of Concentration Ratio 8, measured as 100-CR8.

Table A.2: Negative Binomial Estimation Results Inverse CR4

VARIABLES	(1) Injury Count	(2) Injury Count	(3) Injury Count	
Captain Experience	-0.0890***	-0.0844**	-0.0849**	
	(0.0341)	(0.0356)	(0.0350)	
Last 90 Days	1.872	-0.361*	1.280	
	(1.225)	(0.187)	(1.135)	
Age	0.0978	0.361*	0.377*	
	(0.0759)	(0.209)	(0.219)	
Age x L90D	-0.0493*		-0.0355	
	(0.0280)		(0.0251)	
AGE Squared		-0.00388*	-0.00337	
		(0.00230)	(0.00220)	
Aircraft Weight	0.0288*	0.0327*	0.0317*	
	(0.0160)	(0.0173)	(0.0178)	
Aircraft Age	-0.0760	-0.0822	-0.0798	
	(0.0989)	(0.0967)	(0.0964)	
Dark Flying Conditions	0.950***	0.895***	0.961***	
	(0.290)	(0.306)	(0.296)	
Favorable Flying Conditions	0.435	0.372	0.367	
	(0.403)	(0.433)	(0.408)	
Inverse CR4	0.278*	0.286*	0.283*	
	(0.153)	(0.152)	(0.158)	
Observations	850	850	850	850
Pseudo R-squared	0.1627	0.1641	0.1651	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Variables explained: Captain Experience is the total experience of the captain in thousands of hours. Last 90 Days is the total number of (hundred) hours the captain has flown the past 90 days. Age is the age of the captain. Aircraft Weight is the aircraft weight in thousands of pounds. Aircraft Age is the aircraft age in thousand of flight hours. Dark Flying Conditions is a dummy variable equal to 1 if the flight is operated under dark flying conditions, and 0 otherwise. Favorable Flying Conditions is a dummy variable equal to 1 if the flight is operated under visual flight conditions, and 0 otherwise. Inverse CR4 is the inverse of Concentration Ratio 4, measured as 100-CR4.

Appendix B. Appendix for Chapter 2

Appendix B.1. Pilot Training Additional Information

The following information in this section has been retrieved from the Federal Aviation Administration's website.

In the United States, pilots have to obtain several licenses to be able to operate. The private pilot license is the first step. This license allows a person to become pilot-in-command of a single-engine aircraft after having taken a written and practical exam after having accomplished of a legal minimum of 40 hours of flight, with at least 10 hours solo and 20 hours with a Certified Flight Instructor (CFI). This license carries a visual flying rating (VFR), which permits aircraft operation in clear weather conditions only since navigation is done by sight.

The next step is for the student to obtain an instrument flying rating (IFR). This add-on rating is not a separate license. It allows a pilot with a private pilot license to operate a single engine aircraft in deteriorated weather. Pilots learn to use their instruments to navigate despite a reduction in visibility due to rain, fog, haze, or low clouds. An instructor that provides training for this rating is called a CFII, where the second letter I is for "instrument." The exam also requires the completion of a written and practical component but can only be taken after logging at least 50 hours of cross-country flight as Pilot-In-Command, and 40 hours of instrument time which includes a minimum of 15 hours of instrument flight training. This step is crucial, as all flights 18,000 feet above mean sea level, such as commercial- and private jet flights requires pilots to have this rating.

To obtain the commercial pilot license, the pilot must have completed a minimum of 250 hours of flight time, with at least 100 hours of pilot-in-command. With this license, a pilot is restricted to fly for hire clients with the restrictions of being within 50 miles from the original airport and must operate within VFR rules. Similarly, the exam has a written and practical component.

Next, student pilots complete add-ons where they obtain their Multi-Engine rating. As obvious as it sounds, it allows a pilot to go from a single engine aircraft to a multi-engine one. Training requires a double engine plane, which can go higher, faster, and further. This option is available for both VFR and IFR licenses as Pilot-In-Command.

After having completed 1,500 hours, with 500 hours of cross-country time, 100 hours of night flight, 50 hours of multi-engine, and 75 hours of instrument flying, a pilot is now eligible to obtain the Airline Transport Pilot (ATP). Obtaining the ATP must be done after receiving the commercial license and instrument rating. This license is required to work as a commercial pilot in an airline. Many pilot students who want to reach their 1,500 hours fast and at a lower cost to make a profession out of flying do so by the route of CFI because instruction time is logged as Pilot-In-Command hours. It should be made stated that after the Colgan Air crash in February 2009, Congress had passed PL 111-216 (in August 2010) to take safety measures including increasing the number of flight hours required from 250 to 1,500 before joining a FAR Part 121 operation. Of course, PL 111-216 also includes other measures that are airline specific. Further pathways to build flight hours are [5]:

- To operate in Part 125 as Second-in-Command or co-pilot, which is flying private jets (this requires a type rating discussed below)
- Part 135, which is the operation of commercial aircraft of up to 30 passengers [6]
- Part 137, which is flying for agricultural purposes

However, there are exemptions on the number of hours. For instance, if a flying school is accredited to provide an associate degree or a bachelor's degree, then the total hour requirement falls to 1,250 and 1,000 hours respectively, which would grant the pilot an R-ATP. The above licenses and ratings can be obtained either through a part 61 school, which is a learn as you go, or a part 141 school, which follows a strict course structure approved by the FAA.

[5] these are not the norm.

[6] These hours do not count as PIC unless the pilot is a captain, instructor, or examiner

Appendix C. Tables and Figures

Table C.1: Delta Airlines Captain Pay Scale (Hourly)

Year	737-700/800	737-900	757-300	767-300	767-400ER	777	A319/A320	A321	A330-200	B717	MD88	MD90	A350	A330-900
12	284	286	296	296	334	354	274	286	334	256	269	269	354	339
11	282	283	293	293	332	351	272	283	332	254	266	266	351	336
10	280	281	290	290	329	349	270	281	329	252	263	263	349	334
9	278	279	287	287	327	346	268	279	327	250	260	260	346	331
8	276	277	285	285	324	343	266	277	324	248	258	258	343	329
7	273	275	283	283	322	341	264	275	322	246	256	256	341	326
6	271	273	281	281	320	338	262	273	320	244	254	254	338	324
5	269	270	278	278	317	335	260	270	317	242	252	252	335	321
4	267	268	276	276	314	333	257	268	314	240	250	250	333	318
3	265	266	274	274	312	330	255	266	312	238	248	248	330	316
2	263	264	272	272	309	327	253	264	309	236	245	245	327	313
1	261	262	269	269	307	325	251	262	307	235	243	243	325	311

Table C.2: Delta Airlines First Officer Pay Scale (Hourly)

Year	A319	A320	A321	B717	MD88	MD90	A350	B737	B738	B739	B763ER	B764ER	B757	A330-900	A220
12	187	187	195	175	184	184	242	194	194	195	202	228	202	232	180
11	186	186	193	173	182	182	240	192	192	193	200	226	200	229	177
10	183	183	191	171	179	179	237	191	191	191	197	224	197	227	175
9	181	181	189	169	176	176	234	188	188	189	194	221	194	224	172
8	179	179	187	167	174	174	232	186	186	187	192	219	192	222	170
7	175	175	183	164	170	170	226	182	182	183	188	214	188	217	166
6	171	171	178	159	166	166	220	177	177	178	183	208	183	211	162
5	166	166	173	155	162	162	215	172	172	173	178	203	178	206	158
4	162	162	169	152	158	158	210	168	168	169	174	198	174	201	154
3	159	159	165	148	154	154	205	164	164	165	170	194	170	196	150
2	136	136	141	126	131	131	175	141	141	141	145	165	145	168	128
1	92	92	92	92	92	92	92	92	92	92	92	92	92	92	92

Table C.3: Skywest Captain Pay Scale (Hourly)

Year	CRJ200	CRJ700	CRJ900	E175
20	118	125	128	126
19	117	124	127	125
18	116	123	126	124
17	115	122	125	123
16	114	121	123	122
15	112	119	121	120
14	109	116	118	116
13	106	112	114	113
12	103	109	111	110
11	100	106	108	106
10	97	103	105	103
9	94	100	102	100
8	91	97	98	97
7	89	94	96	95
6	86	91	93	92
5	84	89	90	89
4	81	86	88	87
3	79	84	86	84
2	77	82	83	82
1	75	80	81	80

Table C.4: Skywest First Officer Pay Scale (Hourly)

Year	CRJ200	CRJ700	CRJ900	E175
8	62	62	62	62
7	61	61	61	61
6	60	60	60	60
5	59	59	59	59
4	58	58	58	58
3	56	56	56	56
2	51	51	52	52
1	46	46	46	46

Table C.5: Carrier Classification

	Regional Carriers	Minor Carriers	Low Cost Carriers	Legacy Carriers	Cargo
1	Air Wisconsin Airlines	Aloha Airlines	ATA Airlines	Alaska Airlines	ABX Air
2	Business Express	Continental Micronesia	AirTran Airways	America West Airlines	Air Transport International
3	Chautauqua Airlines	Hawaiian Airlines	Allegiant Air	American Airlines	Aloha Airlines
4	Colgan Air	Miami Air International	Frontier Airlines	Continental Air Lines	Amerijet International
5	Comair	North American Airlines	Independence Air	Delta Air Lines	Arrow Air
6	Compass Airlines	Omni Air International	JetBlue Airways	Northwest Airlines	Astar USA
7	Endeavor Air	Tower Air	Kiwi International	Trans World Airways	Atlas Air
8	Envoy Air	USA 3000 Airlines	National Airlines	US Airways	Centurion Cargo
9	ExpressJet Airlines	USAir Shuttle	Reno Air	United Air Lines	Emery Worldwide Airlines
10	GoJet Airlines	Virgin America	Southwest Airlines		Evergreen International
11	Horizon Air		Spirit Airlines		Federal Express Corporation
12	Mesa Airlines		Sun Country Airlines		Florida West Airlines
13	Mesaba Airlines		Valujet Airlines		Gemini Air Cargo Airways
14	Midway Airlines		Vanguard Airlines		Kitty Hawk Aircargo
15	Midwest Airline		Western Pacific Airlines		Kitty Hawk International
16	PSA Airlines				Lynden Air Cargo Airlines
17	Republic Airline				Polar Air Cargo Airways
18	Shuttle America				Southern Air
19	SkyWest Airlines				USA Jet Airlines
20	Trans States Airlines				World Airways

Table C.6: Bankruptcies

	Airline Name	Date Filed	Date Emerged
1	Allegiant Air	2000	2001
2	Aloha Airlines	12/30/2004	02/17/2006
3	America West Airlines	06/27/1991	08/10/1994
4	Amerijet International	08/22/2001	31/12/2001
5	Arrow Air	07/01/2010	0
6	ATA Airlines	10/26/2004	03/01/2006
7	Atlas Air	01/30/2004	07/14/2004
8	Business Express	01/22/1996	04/17/1997
9	Champion Air	03/31/2008	0
10	Colgan Air	04/01/2012	04/17/2013
11	Comair	09/14/2005	0
12	Continental Airlines	12/03/1990	04/16/1993
13	Endeavor Air	04/01/2012	04/17/2013
14	Frontier Airline	04/10/2008	09/10/2009
15	Hawaiian Airlines	03/21/2003	05/18/2005
16	Independence Air	11/07/2005	01/05/2006
17	Kiwi International	09/30/1996	0
18	Mesa Airlines	01/05/2010	01/20/2011
19	Midway Airlines	08/13/2001	10/30/2003
20	National Airlines	12/06/2000	11/06/2002
21	Northwest Airlines	09/14/2005	05/18/2007
22	Republic Airline	02/25/2016	04/20/2017
23	Ryan International Airlines	03/06/2012	0
24	Southern Air Transport	09/28/2012	03/14/2013
25	Sun Country Airline	10/06/2008	12/04/2008
26	Tower Air	02/29/2000	0
27	Trans World Airways	01/10/2001	0
28	Trans World Airways	06/30/1995	08/04/1995
29	US Airways	08/11/2002	03/18/2003
30	US Airways	09/12/2004	09/16/2005
31	Vanguard Airlines	07/29/2002	0
32	Western Pacific Airlines	10/05/1997	02/04/1998

Table C.7: Mergers

	Carriers	Date
1	AirTran and ValueJet	1998
2	American Airlines and Reno Air	1999
3	Delta Airlines and Atlantic Southeast Airlines	1999
4	American Airlines and Trans World Airways	2001
5	US Airways and America West Airlines	2007
6	Southwest Airlines and ATA Airlines	2007
7	Republic Airline and Midwest Airlines	2008
8	Delta Airlines and Comair	2010
9	ExpressJet & SkyWest Airlines	2011
10	United Airlines and Continental Airlines	2012
11	Endeavor Air and Mesaba Airlines	2012
12	Southwest Airlines and AirTran Airways	2012
13	Alaska Airlines & Virgin America	2012
14	Shuttle America and Chautauqua Airlines	2014
15	American Airlines and US Airways	2015
16	Republic Airline and Shuttle America	2017

Table C.8: Estimated Number of Pilots

Year	ATPL	Commercial Airlines
2005	141,992	74,475
2006	141,935	74,039
2007	143,953	73,488
2008	146,838	75,599
2009	144,600	72,009
2010	142,198	73,681
2011	142,511	71,372
2012	145,590	73,494
2013	149,824	74,411
2014	152,933	75,778
2015	154,730	76,437
2016	157,894	80,071
2017	159,825	83,072
2018	162,145	87,004

Figure C.1: Key Variables over Time

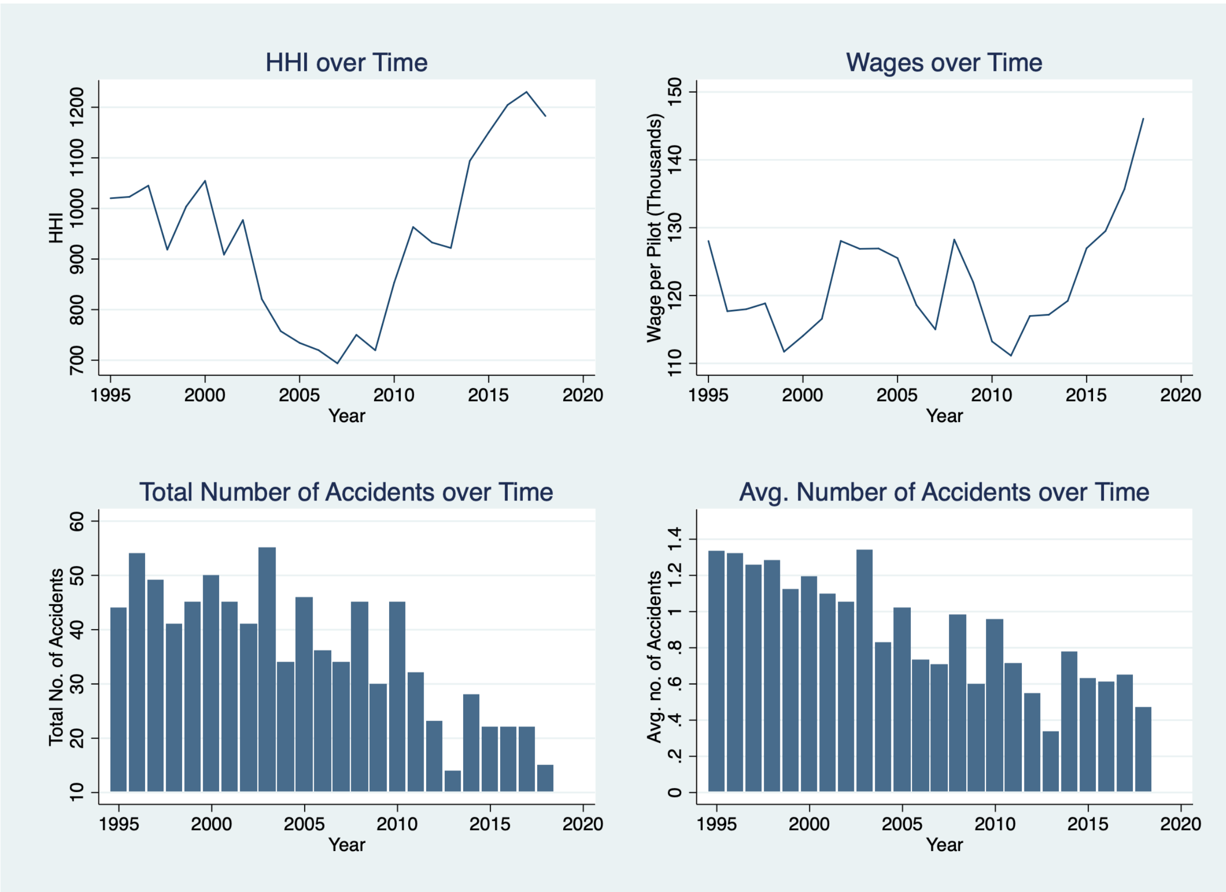


Figure C.2: Key Relationships

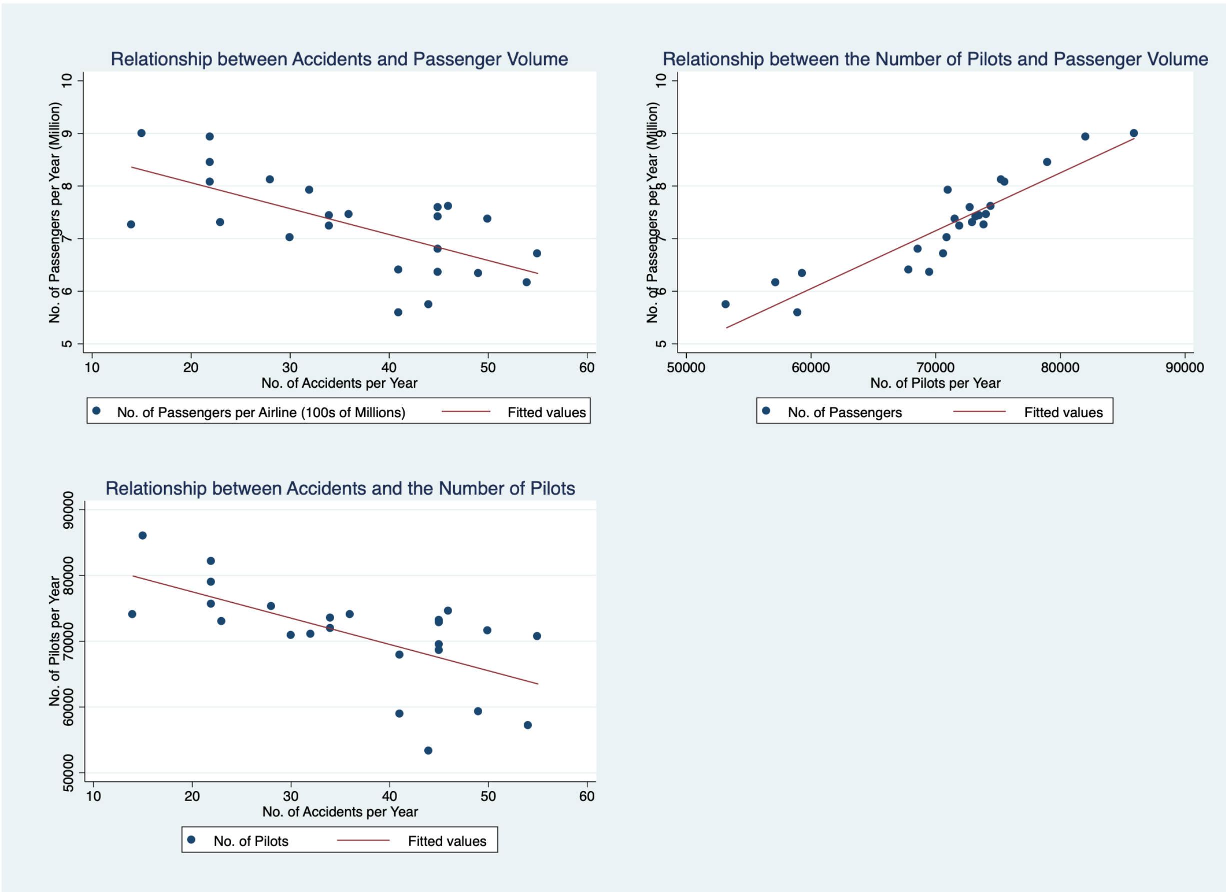


Figure C.3: Monopsony in the Labor Market (static)

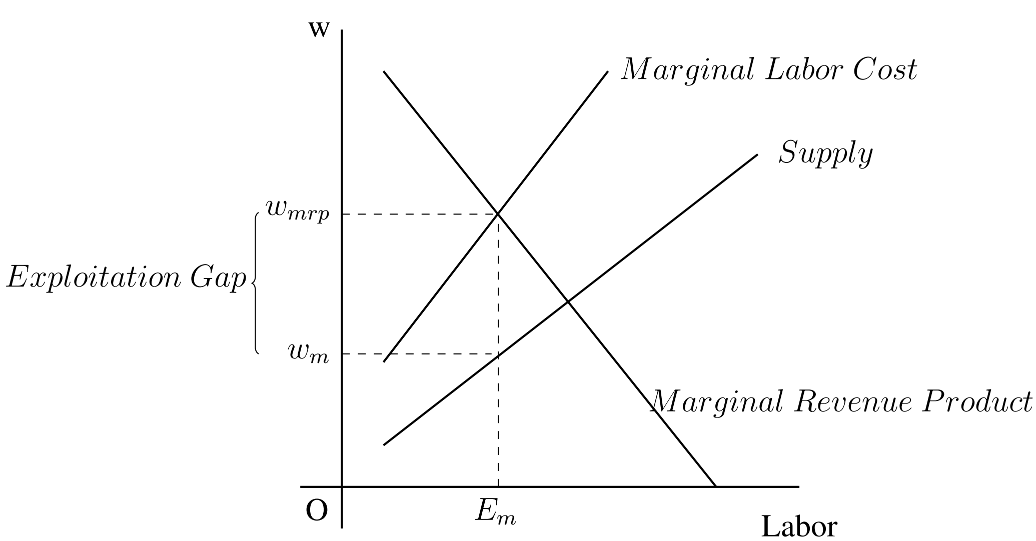


Table C.9: Estimating the Wage Elasticity (Cargo Carriers)

	(1) OLS	(2) 2SLS	(3) 1st stage: log no. pilots
Log Number of Pilots	-0.175	-1.061	
	(0.102)	(2.855)	
Union membership	0.202	0.586	0.445*
	(0.170)	(1.298)	(0.215)
Bankruptcy protection	-0.351*	0.223	0.566***
	(0.136)	(1.587)	(0.0933)
Competition	0.00161	0.00415	0.00238*
	(0.00166)	(0.00823)	(0.00102)
Accidents T-1			-0.00771
			(0.0244)
Airline FE	Yes	Yes	Yes
N	251	229	229
Underidentification		0.114	
Weak identification		0.100	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure C.4: Pilot Wage Simulation

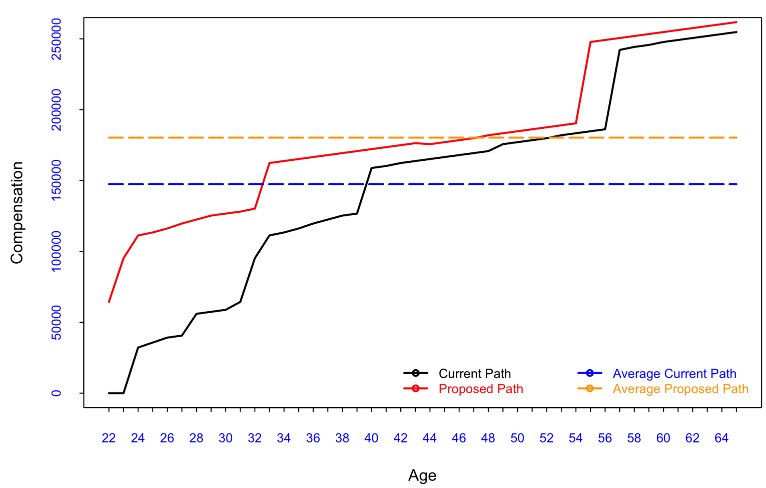


Table C.10: 2SLS First-stage Results

	(1) Log No. Pilots	(2) Log No. Pilots	(3) Log No. Pilots*Comp
Accidents T-1	0.0409***	-0.0444	-3.987***
	(0.00805)	(0.0610)	(0.598)
Union membership	0.399***	0.409***	4.084**
	(0.0836)	(0.0898)	(1.401)
Bankruptcy protection	-0.0633	-0.0757	-0.453
	(0.0734)	(0.0762)	(0.869)
Merger event	0.104	0.113	0.970
	(0.0666)	(0.0669)	(0.771)
Competition Index (Std.)	0.574***	0.571***	12.69***
	(0.101)	(0.101)	(1.032)
IHS of Net Income in 10s of Millions	0.0101	0.00679	0.151
	(0.00733)	(0.00760)	(0.0778)
Low-cost carrier	-1.249***	-1.254***	-11.56***
	(0.0943)	(0.0984)	(1.473)
Regional carrier	-2.529***	-2.532***	-24.00***
	(0.0714)	(0.0733)	(0.729)
Minor carrier	-2.218***	-2.223***	-20.40***
	(0.0987)	(0.101)	(1.169)
Accidents T-1 * Competition		0.0000929	0.00478***
		(0.0000627)	(0.000594)
Airline FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	617	617	617

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.11: Sample Characteristics: Passenger vs. Cargo

	All Carrier Types			
	Mean	Std. Dev.	Min	Max
Number of pilots	1846	(2584)	27	13,621
Wage	124,165	(60,164.3)	11,892.7	556,126
Accidents	.95	(1.8)	0	11
Union membership	.74	(.44)	0	1
Net Income (10s of Millions)	7.2	(164)	-2,705	2,822
N	912			
	Passengers			
	Mean	Std. Dev.	Min	Max
Number of pilots	2230	(2838)	60	13,621
Wage	117,519	(54,950.2)	16,897.6	278,310
Accidents	1.1	(2)	0	11
Union membership	.85	(.36)	0	1
Net Income (10s of Millions)	6.2	(191)	-2,705	2,822
Competition Index	9,067	(162)	8,767	9,305
N	665			
	Cargo			
	Mean	Std. Dev.	Min	Max
Number of pilots	849.1	(1263)	27	4,392
Wage	141,210	(71,316.3)	11,892.7	556,126
Accidents	.42	(1.2)	0	9
Union membership	.46	(.5)	0	1
Net Income (10s of Millions)	10	(33)	-36	197
Competition Index	6,990	(948)	5,768	8,716
N	232			

Note: Total number of observations: Airline x Year.

Table C.12: Sample Characteristics: Legacy Carriers

	Legacy Carriers			
	Mean	Std. Dev.	Min	Max
Number of pilots	5654	(3419)	892	13,621
Wage	182,849	(36,952.5)	87,143.1	278,310
Accidents	3.2	(2.6)	0	11
Union membership	1	(0)	1	1
Net Income (10s of Millions)	6.8	(380)	-2,705	2,822
N	166			

Table C.13: Sample Characteristics: Low-Cost Carriers

	Low-cost Carriers			
	Mean	Std. Dev.	Min	Max
Number of pilots	1387	(1873)	61	8,940
Wage	126,189	(42,504.4)	37,778.9	255,554
Accidents	.7	(1.4)	0	7
Union membership	.66	(.47)	0	1
Net Income (10s of Millions)	17	(51)	-83	357
N	160			

Table C.14: Sample Characteristics: Regional Carriers

	Regional Carriers			
	Mean	Std. Dev.	Min	Max
Number of pilots	1165	(868.7)	109	4,257
Wage	69,762.1	(20,646.1)	16,897.6	177,276
Accidents	.43	(.85)	0	7
Union membership	.89	(.31)	0	1
Net Income (10s of Millions)	.045	(15)	-178	44
N	258			

Table C.15: Sample Characteristics: Minor Carriers

	Minor Carriers			
	Mean	Std. Dev.	Min	Max
Number of pilots	270.4	(185.1)	27	824
Wage	124,607	(38,339.5)	58,902.6	362,056
Accidents	.14	(.44)	0	3
Union membership	.81	(.39)	0	1
Net Income (10s of Millions)	2.1	(8.3)	-16	38
N	91			

Note: Total number of observations: Airline x Year.

Table C.16: Firm Characteristics by Union Status

	Non-Union Mean	Union Mean
Number of pilots	801	2,489
Wage	92,772	121,944
N	103	563

Table C.17: Estimating the Wage Elasticity (Passenger Carriers)

	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
Log Number of Pilots	0.0281	0.400**	0.0194	0.391**
	(0.0678)	(0.130)	(0.0675)	(0.126)
Union membership	0.200**	0.0637	0.200**	0.0691
	(0.0603)	(0.0824)	(0.0706)	(0.0891)
Bankruptcy protection	0.113	0.125	0.102	0.113
	(0.0573)	(0.0649)	(0.0549)	(0.0637)
Merger event	-0.134	-0.173*	-0.127	-0.166*
	(0.0787)	(0.0697)	(0.0774)	(0.0680)
Competition Index (Std.)	-0.227	0.149	-0.0513	0.322*
	(0.114)	(0.138)	(0.142)	(0.136)
IHS of Net Income (10s of Millions)	0.000770	-0.00362	-0.00248	-0.00668
	(0.00427)	(0.00530)	(0.00444)	(0.00472)
Low-cost carrier	-0.250*	0.289	-0.270*	0.273
	(0.106)	(0.181)	(0.111)	(0.181)
Regional carrier	-1.242***	-0.177	-1.262***	-0.194
	(0.178)	(0.336)	(0.178)	(0.323)
Minor carrier	-0.342*	0.566	-0.373*	0.540
	(0.161)	(0.296)	(0.162)	(0.290)
Competition Index (Std.) * Log Number of Pilots			-0.0245*	-0.0239
			(0.00948)	(0.0124)
Airline FE	Yes	Yes	Yes	Yes
N	665	617	665	617
Underidentification		8.766		8.745
Weak identification		25.62		12.57

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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