An Evaluation of Legislation Designed to Improve Airline Pilots' Safety and Performance*

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February 2024

Abstract

H.R. 5900, which was passed by Congress in July 2010, legislated more restrictive pilot rest requirements and increased the number of pilot training hours required to obtain an airline transport pilot license. This paper examines the effect that raising the occupational licensing standards have had on airline service quality. A priori, the effect is ambiguous since putting in place more restrictive licensing requirements reduces the available pool of replacement pilots and may cause airline pilots to behave opportunistically and put forth less effort, which suggests a detriment to on-time performance. On the other hand, well-rested and more experienced pilots may provide enhanced productivity leading to improved on-time performance. Our event study analysis surrounding the effective date of H.R. 5900 (August 2013) shows an increase in traditional delays in the short run amid an ongoing pilot shortage, while extended delays were also exacerbated in the short run as a result of binding work schedule restrictions.

JEL classifications: J44, K23, L15
Keywords: Labor relations, Occupational licensing, Product quality, Airlines

*We would like to thank the editor and two anonymous referees, Jan Brueckner, Morris Kleiner, Paulos Lakew, Brad Larsen, Alexander Luttmann, John Pencavel, Jeffrey Prince, David Pyke, Jonathan Williams, as well as participants at the INFORMS Annual Meeting and the Southern Economic Association Annual Meeting. We would also like to thank several industry contacts who provided valuable institutional background knowledge.

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1 Introduction

A larger proportion of the U.S. workforce is impacted by occupational licensing than either minimum wage or unionization (Kleiner, 2000). The goal of occupational licensing is to protect the public from "incompetent, untrustworthy, or irresponsible practitioners" (Gittleman and Kleiner, 2016, p.145). Occupational licensing has grown significantly since the 1950s in the U.S., with more than one-third of the workforce either licensed or certified by the government (Kleiner, 1990; Kleiner and Krueger, 2010; Kleiner and Krueger, 2013). The effect of raising occupational licensing standards on quality is ambiguous since a license requirement will eliminate some inexperienced low-quality providers; however, the remaining higher paid licensees now have less incentive to provide high-quality products or service since there are fewer competitors (Kleiner, 2000; Carroll and Gaston, 1981).

While licensing is associated with about 18 percent higher pay (Kleiner and Krueger, 2013) and has been found to reduce the wage gap between natives and immigrants (Cassidy and Dacass, 2021), there is growing empirical evidence that indicates no improvement in quality from stricter licensing standards. Kleiner (2006) suggests that licensing drives up prices and overall wages compared to unlicensed occupations using cross-sectional data yet finds no clear impact of licensing on overall quality. Farronato et al. (2020) find more stringent regulations are associated with less competition, higher prices, and no improvement in customer satisfaction when examining an online platform for home improvement services.

There are two studies from the health care industry that also find no relationship between service quality and licensing standards. Kleiner and Kudrle (2000) find that states with stricter dental licensing standards do not have improved dental outcomes, yet these stricter standards are associated with higher dental wages. Kleiner et al. (2016) show that the relaxation of occupational licensing laws for nurse practitioners has led to higher wages for nurse practitioners and lower wages for physicians, while not adversely affecting the quality of patient care since neither mortality rates nor liability insurance premiums have changed. To be sure, all of these studies can only assess the impact of regulatory interventions on observed quality and it is certainly possible that there were impacts on quality dimensions that are unobserved by the econometrician. In fact, Carroll and Gaston (1981) find evidence across several occupations and trades (e.g. electrical, plumbing, real estate, dentistry, and veterinarian) that restrictive licensing requirements are detrimental to service quality. More recently, Kleiner (2013) finds more stringent licensing requirements of electricians and plumbers have little impact on worker safety. Larsen et al. (2020) suggest that more stringent teacher licensing raises the lower tail of quality for secondary school teachers while having no effect on average quality. Our paper studies how changes to occupational licensing requirements impact the quality of service provided by airline captains and first officers.

We perform an event study to analyze the ramifications of increased regulations on pilot training and work schedules in H.R. 5900, a law that was unanimously passed by both the U.S. House of Representatives and the U.S. Senate. Since quality is multi-dimensional (Hjorth-Andersen, 1984), we consider the impact of H.R. 5900 across a variety of quality dimensions. The primary objective of H.R. 5900 was to improve quality through enhanced safety and this objective appears to have been achieved since there have been no fatal domestic airline crashes due to pilot error since this legislation went into effect. H.R. 5900 also impacted the on-time performance of airlines, which is the focus of this study. In a similar fashion as Prince and Simon (2015, 2017) and Lee and Rupp (2007), we also use on-time performance as a proxy for quality in the airline industry by tracking two performance measures: 1) flights that arrive at least 15 minutes late (the traditional delay definition) and 2) flights that arrive at least 180 minutes late (the European Union's definition of an extended delay). Our empirical investigation will determine if these product quality measures are complements or substitutes.

We find evidence that higher occupational licensing standards for pilots negatively impacted productivity in the short run since airlines experienced an increase in traditional delays. This result is consistent with the claim that raising the occupational licensing standards allows for opportunistic behavior by employees as pilots maybe providing less effort given the scarcity of replacement pilots. Moreover, we find increases in extended delays, which may reflect the difficulty that carriers have in locating replacement crews when pilots reach their daily maximum flight time limits.

In sum, these results highlight the multi-dimensionality of product quality. We find that product quality measures are substitutes since increased occupational licensing standards improves some aspects of quality (safety), while decreasing other quality attributes (on-time performance).

2 H.R. 5900 Legislation

The crash of Colgan Air flight 3407 on February 12, 2009 in Buffalo, New York tragically took the lives of all 49 passengers and crew on board in addition to a person whose house was struck by the plane.[1] The ensuing NTSB Accident Report (AAR-10/01) indicated that pilot error was the likely culprit, while pilot fatigue may have also contributed since the cockpit voice recorder indicated a yawn by the co-pilot minutes prior to the crash.[2]

As a consequence of this Colgan Air crash, legislation H.R. 5900 was approved in July 2010, which increased the minimum number of hours for a prospective first officer to obtain an airline transport pilot (ATP) license from 250 hours to 1,500 hours. In fact, this law is commonly referred to as "the 1,500 hour rule" among industry insiders like pilots and operational staff. Additionally, this legislation implemented a 9-hour minimum rest period prior to the flight duty period, while mandating that a pilot must have an opportunity for eight hours of uninterrupted sleep during the rest period.[3] This change constitutes a one hour increase in rest compared to the previous pilot rest rule, while the uninterrupted eight hours of sleep opportunity represents a new initiative. Maximum flight time limits were also set to either eight or nine hours depending on when the pilot is scheduled to begin their initial shift. Finally, the new rule implements maximum flight duty period limits based on the number of flight segments, while the previous rest rule did not consider the number of flight segments.

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[1] Borenstein and Zimmerman (1988) find the total social cost of a fatal aviation accident is considerably larger than the average firm reduction in equity value of 1 percent (or $4.5 million).

[2] According to its official accident report, the National Transportation Safety Board determined that "the probable cause of this accident was the captain's inappropriate response to the activation of the stick shaker, which led to an aerodynamic stall from which the airplane did not recover." (National Transportation Safety Board Accident Report/AAR-10/01, PB2010-91401. February 2, 2010).

[3] For more details see the FAA Fact Sheet - Pilot Fatigue Rule Comparison, 21 December 2011, `https://www.faa.gov/news/fact_sheets/news_story.cfm?newsKey=12445`.

2.1 Enhanced Training Requirements

H.R. 5900 mandated that pilots seeking to become first officers at airlines flying more than nine passengers on a flight must now meet the following three training conditions:

1. Have at least 1,500 hours total time as a pilot.

2. Complete an Airline Transport Pilot Certification Training Program (ATP CTP) with expanded training in risk-assessment and responding to emergency situations, including how to recover from a stall that led to the crash of Colgan Air flight 3407.

3. Additionally, first officers must have at least 1,000 hours as SIC ("second in command") before becoming a captain.

Increasing the minimum number hours of training before a pilot can obtain an ATP license should improve pilot safety and competence. To be sure, this paper investigates the effect of the H.R. 5900 legislation on on-time performance and not safety since there have not been any fatal accidents due to pilot error since the Colgan Air crash in 2009. Indeed, industry insiders we interviewed proudly lauded the recent safety record in the U.S. airline industry. Therefore, we cannot use accidents as a measure to estimate the effect of H.R. 5900 on safety.

The FAA, however, does collect data on "incidents" which occur more frequently than accidents yet still do not occur with enough frequency for meaningful analysis. The FAA distinguishes an accident from a safety incident as follows: an accident occurs when there is a serious injury (hospitalization of greater than 48 hours and/or death) or damage to the aircraft which exceeds $500.[4] On the other hand, an incident is something much more minor that "affects or could affect the safety of operations."[5] Table 1 reports the number of incidents by airline during our sample time period. Given the lack of variation in incidents while keeping in mind that there is an average of nearly 5.5 million flights per year by our sample airlines combined, we do not believe that

[4] http://www.faraim.org/faa/far/CFR-2015-title49-vol7-part830.pdf/

[5] According to a conversation with a United captain, an incident is "something that is 'just embarrassing' for pilots, such as the plane slipping off the taxiway."

incidents are a feasible outcome variable to study the effect of H.R. 5900. Instead, the objective of this paper is to focus on a different dimension of quality that is also important for passengers: timeliness.

Table 1: Number of Incidents

	Airline	2010	2011	2012	2013	2014	2015	2016	2017	2018	TOTAL
Major Airlines	Alaska Airlines	0	3	0	0	0	2	0	2	1	8
	American Airlines	4	6	6	3	5	1	3	2	0	30
	Continental Airlines	0	2	2	0	1	0	0	0	0	5
	Delta Air Lines	13	13	12	8	7	2	2	2	3	62
	United Airlines	15	5	4	3	10	3	3	5	7	55
	US Airways	9	5	6	2	3	0	0	0	0	25
Low-Cost Carriers	AirTran Airways	2	3	0	0	0	0	0	0	0	5
	Allegiant Air	4	1	4	1	1	3	7	4	10	35
	Frontier Airlines	2	1	0	2	1	3	0	1	1	11
	JetBlue Airways	2	0	1	3	4	0	1	1	1	13
	Southwest Airlines	9	13	8	3	5	1	2	5	3	49
	Spirit Airlines	2	0	1	0	1	0	1	1	0	6
	Virgin America	0	1	0	0	0	1	1	1	0	4
Regional Airlines	Endeavor Air	0	0	0	0	1	0	0	0	1	2
	Envoy Air/ American Eagle	4	6	5	6	4	2	4	1	1	33
	ExpressJet	12	8	9	6	4	2	0	1	0	42
	Mesa Airlines	3	2	1	0	1	0	0	5	0	12
	Midwest Airlines	0	0	0	0	0	0	0	0	0	0
	PSA Airlines	3	5	3	3	1	0	4	3	0	22
	Republic Airlines	6	2	1	5	4	4	3	3	2	30
	SkyWest Airlines	9	5	5	3	1	1	3	4	0	31
	TOTAL	99	81	68	48	54	25	34	41	30	480

Source: FAA Accident and Incident Data System (AIDS). `https://www.asias.faa.gov/apex/f?p=100:12:::NO:::`

An unintended consequence of mandating enhanced training requirements is a short-term pilot shortage since this legislation poses a higher hurdle for prospective pilots before becoming a first officer. Following the implementation of H.R. 5900, Great Lakes Airlines[6] and Republic Airways[7] declared bankruptcy in 2018 and 2016, respectively, and both regional airlines cited the lack of available pilots as the primary reason for their bankruptcy filing.

[6]https://www.prnewswire.com/news-releases/great-lakes-airlines-shuts-down-operations-indefinitely-300620781.html, last accessed 27 May 2020.

[7]https://money.cnn.com/2016/02/26/news/companies/pilot-shortage-bankruptcy/index.html, last accessed 27 May 2020.

Table 2: FAA Airline Transport Pilot Licenses

	2010	2011	2012	2013	2014	2015	2016	2017	2018
Active Airmen Certificates Held	142,198	142,511	145,590	149,824	152,933	154,730	157,894	159,825	162,145
Airmen Certificates Issued	3,072	4,677	6,396	8,346	7,749	6,544	9,520	4,449	5,795

Source: U.S. Civil Airmen Statistics. `https://www.faa.gov/data_research/aviation_data_statistics/civil_airmen_statistics`

Although we are unable to obtain hiring or staffing data for individual airlines, the FAA provides data on the total number of active ATP licenses and the amount of new ATP licenses issued from 2010 to 2018, which appear in Table 2.[8] The number of ATP licenses issued unsurprisingly increased from 2010 to 2013 as prospective pilots were incentivized to complete their training before the new rules became effective in July 2013. In subsequent years, there was a decrease in the number of newly issued ATP licenses after the effective date of H.R. 5900. Table 2 shows the number of newly issued Airmen Certificates in 2014 dropped by 597 (7%) and further fell by 1,205 (18%) in 2015. Hence, the enhanced training requirements led to a reduction in newly certified pilots in the short run (i.e. initial two years after the regulation went into effect). One potential implication of this pilot reduction is it provides an opportunity for pilots to behave opportunistically given the lack of available replacement pilots. Finally, the pilot reduction was short-lived as the number of new certificates issued rose sharply in 2016 and fluctuated thereafter.

2.2 Increased Employee Rest Requirements

In addition to increasing the number of flight hours required for training before a pilot can begin their professional career, H.R. 5900 also increased employee rest restrictions for existing pilots and limited the number of daily flight segments that they can fly. In summary, H.R. 5900 also stipulated the following three changes to pilot scheduling/rest requirements based on flight time in the previous 24 hours:

[8] To be sure, the number of active airmen certificates held in a given year does not necessarily equal the sum of the number of active licenses and newly issued licenses in the previous year due to the number of lapsed pilots who retire, fail their medical exam, or decide to not stay current with their license for some other reason.

1. 9 consecutive hours of rest for less than 8 hours of scheduled flight time.
2. 10 consecutive hours of rest for between 8 and 9 hours of scheduled flight time.
3. 11 consecutive hours of rest for more than 9 hours of scheduled flight time.

Since the rest requirements applied to all pilots, these restrictions make it more difficult for airlines to find last minute replacements for pilots and flight crews. Hence, minor flight delays that cause a pilot to time-out can now ultimately lead to extended flight delays. To maintain their on-time performance, carriers would need more stand-by replacement crews to be on call as pilots reach duty time limits due to flight delays. Prior to stepping foot on the aircraft, every pilot must certify that they are not too fatigued to fly. The H.R. 5900 legislation changed the stigma attached to pilot fatigue since it is now non-punitive for a pilot to call in fatigued, whereas pilots previously would have their pay docked for missing flights due to fatigue.

Since a variety of factors can contribute to a flight being delayed beyond the control of the airline pilot, we examine the subset of morning flights (from 5:00AM to 9:00AM) since the initial morning flight eliminates one primary delay cause: late arriving aircraft. In addition, morning flights are not subjected to another prevalent flight delay cause: delays that propagate/cascade during the day (Dou et al., 2020; Rupp, 2009). While weather delays are possible in the morning, weather induced delays are less likely since both thunderstorms and heat induced delays are afternoon phenomena (Adler, 2021). Therefore, we expect that flight delays induced by increased employee rest restrictions to be more prevalent for morning flights.

The aviation industry is not alone in adjusting its rest requirements since both the trucking industry and medical residency profession have recently imposed stricter duty hour limitations in an effort to prevent employee fatigue and improve safety. These changes were prompted due to growing evidence of the dangers posed by fatigued employees. For example, a sleep study of long-haul truck drivers revealed that truckers obtained less sleep than required for alertness on the job with the highest risk of sleeping on the job occurring late night and early morning (Mitler et al., 1997). In the medical profession, interns that have just worked shifts of extended duration (24 hours or more) have a significantly higher likelihood of being involved in a motor vehicle accident compared to non-extended shifts (Barger et al., 2005).

The benefits from reducing the number of consecutive hours working may extend beyond improving safety since less fatigued employees may also be more productive. Whether employees are working in modern day call centers (Collewet and Sauermann, 2017) or in ammunitions plants in Britain during World War I (Pencavel, 2015), both studies find a similar result − as the number of hours worked increases, employees become less productive. Beyond employee fatigue on an extended shift, Pencavel (2018) presents considerable evidence that longer hours of work have adverse effects on worker health and quality of life. Pencavel (2016) suggests that worker productivity suffers after a long working week if workers do not have adequate time off from the job to restore their physical, mental, and emotional well-being. Understanding the relationship between hours and output productivity is important because this relationship is a key determinant of future economic growth (Denison, 1962).

3 Empirical Analysis

3.1 Data

Our primary data set is the On-Time Performance Data, which is published monthly by the U.S. Department of Transportation. The raw data provides information on every scheduled domestic flight by carriers with at least 1% market share in the U.S. We observe the flight's carrier, origination and destination airports, as well as scheduled and actual departure and arrival times. Following Forbes et al. (2019), we exclude cancelled or diverted flights along with flights that depart or arrive more than 60 minutes early in order to resolve possible data entry issues.

The cause of a flight delay can be characterized into five broad categories (in order of frequency): 1) late aircraft (e.g. previous flight arrived late causing subsequent flights to be late); 2) carrier (e.g. maintenance or crew problems, aircraft cleaning, baggage loading, or fueling); 3) national air system (e.g. abnormally heavy traffic volume at the airport or air traffic control); 4) weather (e.g. tornado, blizzard, or hurricane); and 5) security (e.g. security breach or evacuation of a terminal).[9] We aggregate these observations to the carrier-route-year-month level in order to calculate the proportion of delays that are attributed to either the pilot or airline. To be sure, the increased regulations on pilot training and work schedules in the H.R. 5900 law potentially impact delays that are classified as either carrier or late aircraft delays. Moreover, the cause of delays are not mutually exclusive since there are cases in which a delay is attributed to multiple reasons. Delays that are attributed exclusively to the national air system (NAS), weather, and/or security issues are unaffected by the regulations established by H.R. 5900.

Although there are several measures of service quality in the airline industry, we proxy for product quality by using two measures for flight delays that have been defined by American and European aviation authorities.[10] First, we employ the industry standard delay definition of flights that arrive 15+ minutes after their scheduled arrival time. Moreover, flight delays are based on arrival time since airline passengers (especially those making connections) are more concerned about arrival delays than departure delays. Second, since neither the U.S. Department of Transportation nor the Federal Aviation Administration specify guidelines for an extended delay, we adopt the European Union's measure of an extended delay: flights that arrive 180+ minutes after their scheduled arrival time.[11]

We append the data on delays with the T-100 data set, which is also published monthly by the U.S. Department of Transportation. This data set is used to calculate the total number of scheduled flights at both the origin and destination airports for a given route (defined as a directional airport-pair). We also collect relevant dates for airlines who have filed for Chapter 11 bankruptcy protection from various public sources.

[9] According to a March 2020 report by the U.S. Department of Transportation, aircraft arriving late (40%) was the most common cause of a delayed flight in 2019 followed by air carrier delay (31%), national aviation system (NAS) delay (24%), extreme weather (6%), and security delay (0%). See AhmadBeygi et al. (2008) and Dou et al. (2020) for an examination of how delays propagate in airline networks.

[10] Forbes et al. (2015), Prince and Simon (2017), and Rupp and Tan (2019) use flight delays as their proxy for product quality.

[11] The European Union's Air Passenger Rights stipulates that passengers be compensated if their flight is delayed by more than three hours. https://europa.eu/youreurope/citizens/travel/passenger-rights/air/index_en.htm

Table 3: Summary Statistics

Variable	Definition	Mean (Std. Dev.)
$Delay15_{ijt}$	Proportion of flights with arrival delays (15+ minutes) due to the pilots or airline for airline i on route j in time period t	0.1289 (0.0891)
$Delay180_{ijt}$	Proportion of flights with extended arrival delays (180+ minutes) due to the pilots or airline for airline i on route j in time period t	0.0063 (0.0128)
$Delay15\_Control_{ijt}$	Proportion of flights with arrival delays (15+ minutes) due to non-aircraft and non-carrier factors for airline i on route j in time period t	0.0616 (0.0604)
$Delay180\_Control_{ijt}$	Proportion of flights with extended arrival delays (180+ minutes) due to non-aircraft and non-airline factors for airline i on route j in time period t	0.0026 (0.0084)
$OriginFlights_{jt}$	Number of flights at origin airport of route j in time period t Note: $OriginFlights\_small = \frac{originflights}{10{,}000}$	9,223.689 (8,282.559)
$DestFlights_{jt}$	Number of flights at destination airport of route j in time period t Note: $DestFlights\_small = \frac{destflights}{10{,}000}$	9,218.532 (8,268.055)
$Bankrupt_{it}$	Dummy variable indicating if airline i is bankrupt in time period t	0.035 (0.1840)
Routes	Number of routes in the sample	5,566
N	Number of observations	509,643

Table 3 reports the summary statistics for the variables used in our empirical analysis. Our final data set covers 21 airlines servicing 5,566 routes in 96 time periods (August 2010 - July 2018) and contains 509,643 observations at the airline-route-year-month level.[12] We find that 12.89% of flights in our full sample experience arrival delays due to the airline and/or pilot ($Delay15$), whereas 0.63% of flights are extended delays ($Delay180$). These values are smaller than the means reported in the existing literature (e.g. Forbes et al., 2015; Prince and Simon, 2017; Rupp and Tan, 2019) since we restrict our attention to the subset of "treatment" delays which are attributed to either the airline or late arriving aircraft.

3.2 Estimation Model

To quantify the impact of raising the occupational licensing requirement from H.R. 5900 on product quality provided in the U.S. airline industry, we implement a fixed effects regression model in which on-time performance serves as the dependent variable. The key variables of interest in

[12]Six major airlines include Alaska Airlines, American Airlines, Continental Airlines, Delta Air Lines, United Airlines, and US Airways. Seven low-cost carriers include AirTran Airways, Allegiant Air, Frontier Airlines, JetBlue Airways, Southwest Airlines, Spirit Airlines, and Virgin America. Eight regional airlines include Endeavor Air, Envoy Air/American Eagle, ExpressJet, Mesa Airlines, Midwest Airlines, PSA Airlines, Republic Airlines, and SkyWest Airlines. Tan (2018) discusses the differences between these three types of airlines.

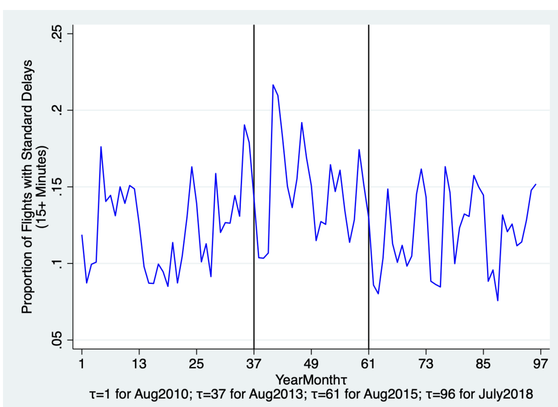
our empirical analysis are the dummy variables that identify the short run and long run effects of the implementation of the H.R. 5900 law. There are three relevant time periods in our analysis based on the passing of H.R. 5900 by the U.S. House of Representatives and the U.S. Senate on July 29, 2010 and July 30, 2010, respectively, and the law becoming effective on August 1, 2013:

1. Post-legislation and pre-enforcement ($HR5900\_baseline$: August 2010 - July 2013)

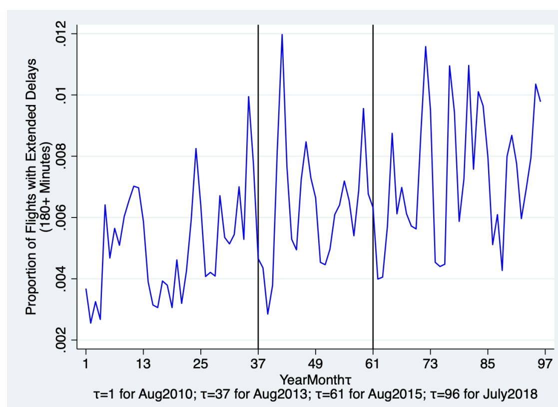
2. Short run effect of legislation ($HR5900\_shortrun$: August 2013 - July 2015)

3. Long run effect of legislation ($HR5900\_longrun$: August 2015 - July 2018)

Figure 1 plots the average value for $Delay15$ (Figure 1(a)) and $Delay180$ (Figure 1(b)) across the 96 time periods in our data set. The two vertical bars demarcate the three relevant time periods with the post-legislation and pre-enforcement time period occurring during YearMonth1 - YearMonth36, the short run effect of our legislation encompassing YearMonth37 - YearMonth60, and the long run effect spanning YearMonth61 - YearMonth96.



(a) Standard Delays (15+ Minutes)



(b) Extended Delays (180+ Minutes)

Figure 1: Time Trend for $Delay15$ vs. $Delay180$

Following Prince and Simon (2017), our basic regression specification is

$$y_{ijt} = \alpha + \sum_{\tau=37}^{96} \beta_\tau YearMonth\tau_t + \delta Controls_{ijt} + \gamma_{ij} + \gamma_{it} + \varepsilon_{ijt}, \tag{1}$$

where y_{ijt} is the on-time performance product quality proxy ($Delay15_{ijt}$ or $Delay180_{ijt}$) for airline i servicing route j in time t. Since the baseline time period ($HR5900\_baseline$) is excluded from the regression, the coefficients for each of the 60 year-month time dummies ($YearMonth\tau$) are interpreted with respect to the three years immediately prior to the implementation of the law.[13] $Controls$ represent a variety of potential delay factors, including airport congestion measured by the number of flights at both the origin airport and destination airport of a route in a given time period ($OriginFlights\_small$ and $DestFlights\_small$)[14] and three dummy variables based on the bankruptcy status of an airline: 1) $Bankrupt\_before = 1$ if the airline files for bankruptcy protection in the following year, 2) $Bankrupt = 1$ if the airline is currently bankrupt, and 3) $Bankrupt\_after = 1$ if the airline exits bankruptcy in the previous year. Finally, we include carrier-route fixed effects (γ_{ij}) and carrier-month fixed effects (γ_{it}), cluster standard errors by carrier-route, and weight our regressions by the number of flights operated by a particular airline on a specific route in a given time period.

Our alternative regression specification is

$$y_{ijt} = \alpha + \beta_1 HR5900\_shortrun_t + \beta_2 HR5900\_longrun_t + \delta Controls_{ijt} + \gamma_{ij} + \gamma_{it} + \varepsilon_{ijt}, \qquad (2)$$

where the main difference between Equations (1) and (2) are the time dummies associated with β. In Equation (1), we conduct an event study analysis by estimating year-month coefficient estimates ($YearMonth\tau$) relative to the baseline time period (three years between the passing of the H.R. 5900 legislation and its effective date). We then create figures that plot the β coefficients and their 95% confidence intervals. On the other hand, we construct $HR5900\_shortrun$ and $HR5900\_longrun$ in Equation (2) as two dummy variables for the short run (YearMonth37 - YearMonth60) and the long run (YearMonth61 - YearMonth96), respectively. As with Equation (1), the baseline time period ($HR5900\_baseline$) is excluded from the regression so the coefficients for both the short run and long run time periods in Equation (2) are interpreted with respect to the three years

[13] As in Prince and Simon (2017), our short run effect time period spans two years, whereas our long run effect time period covers three years.

[14] Mayer and Sinai (2003), Rupp (2009), and Molnar (2013) investigate the role of congestion on flight delays.

immediately prior to the implementation of the law. We then report these regression results in tables to supplement the inference from our event study plots.

3.3 Before and After Comparison

In an effort to improve aviation safety, the H.R. 5900 legislation raised the occupational licensing requirements for airline transport pilots and reduced the maximum possible pilot duty time from nine to eight hours. The primary objective of H.R. 5900 appears to have been achieved given that there have been no fatal aviation crashes due to pilot error since the Colgan Air crash in February 2009.[15] In fact, approximately 5.46 billion domestic U.S. airline passengers were safely transported between August 2010 to July 2018.[16]

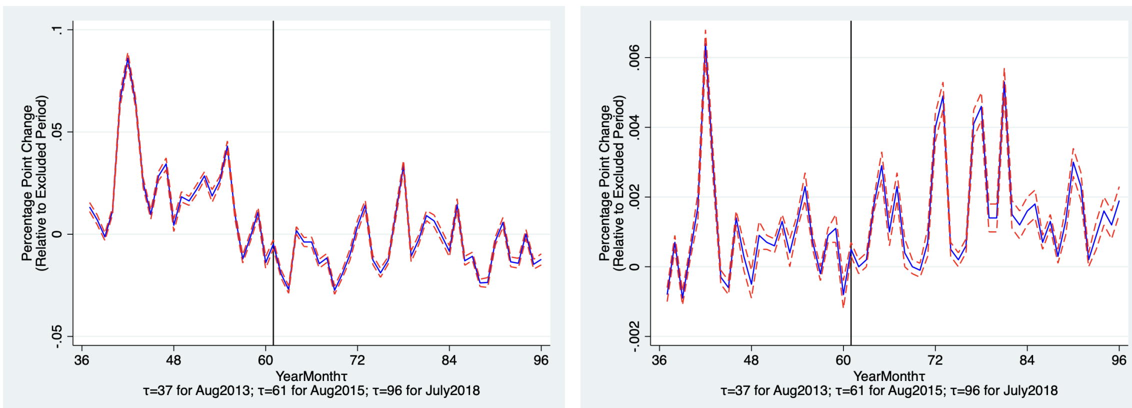
Product quality is multidimensional (Hjorth-Andersen, 1984) and not all quality measures improved following the legislation. An unintended consequence of the H.R. 5900 legislated changes is that employee productivity may change after raising the occupational licensing standards from 250 to 1,500 pilot training hours. Given that the occupational licensing hurdle has been raised which resulted in fewer qualified airline pilots, the remaining pilots may be less diligent in providing on-time performance since there is a thinner pool of replacement pilots. Such a scenario would result in positive estimated coefficients for the time dummies for the 15+ minute arrival delays in Equations (1) and (2), which would be consistent with Carroll and Gaston (1981) who finds that occupational restrictions lower the quality of service received. On the other hand, better trained pilots may be more diligent in their provision of on-time arrivals and hence improve product quality. In this scenario, there would be negative estimated coefficients for the time dummies for the 15+ minute arrival delays.

H.R. 5900 also legislated increased pilot rest requirements and imposed stricter duty time limits (a reduction from nine to eight hours) which could create a binding constraint for airlines since

[15] We are aware of a single aviation fatality between February 2009 and July 2018, which occurred when a Southwest Airlines passenger was struck by a fan blade that broke off mid-flight on April 17, 2018. `https://time.com/5243733/southwest-passenger-commercial-airline-death/`, last accessed 28 May 2020.

[16] Domestic passenger counts come from `https://www.transtats.bts.gov/Data_Elements.aspx?Data=1`, last accessed 27 December 2022.

flight crews could time out with no replacement crews available. As such, an increase in extended flight delays might have nothing to do with employee effort and instead reflect a shortage of qualified replacement pilots. Hence, the binding constraint of a pilot shortage issue can be identified if the estimated coefficients for the time dummies for 180+ minute arrival delays in Equations (1) and (2) are positive and statistically significant.



(a) Standard Delays (15+ Minutes)

(b) Extended Delays (180+ Minutes)

Figure 2: The Effect of H.R. 5900 on On-Time Performance

Figures 2(a) and 2(b) plot the estimated coefficients for the $YearMonth\tau$ time dummies (solid blue line) and their 95% confidence intervals (dashed red line) in Equation (1) using $Delay15$ and $Delay180$ as the dependent variable, respectively. Since the time period post-legislation and pre-enforcement (August 2010 - July 2013) serves as the baseline time period (YearMonth1 - YearMonth36), our event study plots span the short run time period (YearMonth37 - YearMonth60) spanning two years following the effective date of H.R. 5900 (August 2013 - July 2015) followed by the long run time period (YearMonth61 - YearMonth90) spanning three years thereafter (August 2015 - 2018). A vertical bar at YearMonth61 demarcates the short run time period and the long run time period. Since the coefficients for YearMonth37 - YearMonth60 tend to be greater than zero and statistically significant in Figure 2(a) (20 of the 24 coefficients for the short run are positive and significant) and Figure 2(b) (16 of the 24 coefficients for the short run are positive and significant), we determine that both standard delays and extended delays increased in the short run relative to the three years preceding the implementation of the legislation.[17]

Table 4: The Effect of H.R. 5900 on On-Time Performance

	(1) Standard Delays	(2) Extended Delays
$OriginFlights\_small$	0.0171**	-0.0003*
	(0.0014)	(0.0001)
$DestFlights\_small$	-0.0009	-0.0008**
	(0.0013)	(0.0002)
$Bankrupt\_before$	-0.0042**	-0.0008**
	(0.0013)	(0.0001)
$Bankrupt$	-0.0026*	0.0001
	(0.0012)	(0.0001)
$Bankrupt\_after$	0.0064**	-0.0000
	(0.0015)	(0.0001)
$HR5900\_shortrun$	0.0191**	0.0007**
	(0.0007)	(0.0000)
$HR5900\_longrun$	-0.0065**	0.0015**
	(0.0007)	(0.0001)
N	508,942	508,942

Note: *Delay*15, the industry standard definition for a delayed flight (arrival at least 15 minutes late), is the dependent variable in Column (1), whereas *Delay*180, the EU's definition for an extended flight delay (arrival at least 180 minutes late), is the dependent variable in Column (2). Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Table 4 reports the regression results using two time dummies that aggregate the short run ($HR5900\_shortrun$) and long run ($HR5900\_longrun$) in Equation (2). Columns (1) and (2) present the results using *Delay*15, the industry standard definition for a delayed flight, and *Delay*180, the European Union's defintion for a an extended delay, as the dependent variable, respectively. The positive and statistically significant estimate for $HR5900\_shortun$ in Column (1) suggest that there were more delays in the two years after the law took effect compared to the baseline time period (three year time period between the passing of H.R. 5900 and its implementation). Since the estimated coefficients for the time dummies are interpreted as percentage point changes, the numerical values for these estimates are much smaller in magnitude in Column (2) than in Column

[17]Regression results used to plot Figure 2 are reported in in Table A1, which can be found in the appendix of this paper.

(1) given extended delays attributed to pilots and/or airlines (0.63%) occur very infrequently compared to standard delays (12.89%) as reported in Table 3. Nonetheless, the estimated coefficient for $HR5900\_shortun$ in Column (2) is positive and statistically significant, suggesting that the H.R. 5900 law led to a statistically significant increase in extended delays in the short run.

Given that 12.89% of flights are standard delays attributed to the pilot or airline (Table 3), the results in Table 4 are economically significant. For example, an estimated coefficient of 0.0191 for $HR5900\_shortrun$ in Column (1) implies that treatment delays rose by 14.82% in the short run compared to the baseline time period. This result is consistent with Table 2, which shows a decrease in the number of Airmen Certificates Issued in 2014 (-7%) and 2015 (-16%) following the legislation change. Hence, fewer replacements pilots are available, creating an opportunity for pilots to reduce their effort. Moreover, Table 3 also reports that 0.63% of flights experience an extended delay due to the pilot or airline so the estimate for $HR5900\_shortrun$ in Column (2) is also economically significant since treatment extended delays rose by 11.1% relative to the three years preceding the implementation of H.R. 5900.

Finally, we note a slight improvement occurs for standard delays in the long run with an estimate of -0.0065 for $HR5900\_longrun$ (see Column (1) of Table 4). This finding is also supported by Table 2, which shows a substantial increase (45%) in Airmen Certificates issued at the start of the long run period in 2016 that provided airlines with more options to replace shirking/underperforming pilots.

On the other hand, significant extended delays persist in the long run following the legislation. An estimated coefficient of 0.0015 for $HR5900\_longrun$ in Table 4 suggests a 23.8% increase in extended delays three to five years after the law change went into effect, indicating that increased pilot rest requirements continued to have economically significant impacts on flight schedules by contributing to more extended delays. Moreover, this finding also highlights the multi-dimensionality of quality since some quality aspects like safety have improved post-legislation while others have gotten worse due to more frequent extended delays in both short run and long run periods. This suggests that our quality measures of safety and on-time performance are substitutes.

3.4 Analysis of Treatment Group vs. Control Group

Although the analysis in Section 3.3 focuses on delays that are caused by either the pilot or airline, we can determine whether similar patterns exist for these delays, which we refer to as "treatment" delays, and "control" delays that include delays due to non-aircraft and non-carrier factors (i.e. delays attributed to either weather, national air system, or security issues). First, we replace $Delay15$ and $Delay180$ in Equations (1) and (2) with the proportion of flights with control delays ($Delay15\_Control$) and the proportion of flights with extended control delays ($Delay180\_Control$), respectively. If the estimated coefficients when using control delays as the dependent variable are qualitatively similar to those presented from treatment delays in Table 4, then the H.R. 5900 legislation did not influence on-time performance; rather, any observed changes would be a reflection of a secular trend in flight delays. If control delays, however, are affected differently than treatment delays, then such a finding would suggest that the more stringent regulations for airline pilots have impacted airline on-time performance above and beyond what was expected.

In order to analyze differences between treatment delays and control delays, we generate two new dependent variables: $Delay15\_Diff$ and $Delay180\_Diff$ are defined as the difference between treatment delays and control delays using the 15-minute and 180-minute definitions, respectively. For example, we construct $Delay15\_Diff = Delay15 - Delay15\_Control$ and $Delay180\_Diff = Delay180 - Delay\_Control180$. When incorporating either $Delay15\_Diff$ or $Delay180\_Diff$ as the dependent variable in Equations (1) and (2), the results suggest that the proportion of treatment delays increased by more than the proportion of control delays if the coefficients for the time dummies are positive. On the other hand, if the coefficients for the time dummies are negative, then the proportion of treatment delays fell by a larger amount than the proportion of control delays. Finally, the law had the same effect on both types of delays if the coefficients for the time dummies are insignificant.

Table 5 reports the results of the treatment and control delays based on the industry standard definition for a delayed flight (arrival at least 15 minutes late). By construction, Column (1) in Table 5 is identical to Column (1) in Table 4, which reports the results of Equation (2) using

$Delay15$ as the dependent variable. Column (2) in Table 5 uses $Delay15\_Control$, which is the proportion of flights with control delays (15+ minutes), as the dependent variable. So Column (1) includes traditional treatment delays that are attributed to the pilot or airline, whereas Column (2) includes traditional control delays associated with weather, national air system, or security issues. The coefficient for $HR5900\_shortrun$ is larger in Column (1) than in Column (2), suggesting that H.R. 5900 appears to have a stronger positive effect (i.e. worse product quality) on traditional treatment delays than traditional control delays in the long run.

Table 5: Treatment Delays vs. Control Delays

	(1) $Delay15$	(2) $Delay15\_Control$	(3) $Delay15\_Diff$
$OriginFlights\_small$	0.0171**	-0.0049**	0.0220**
	(0.0014)	(0.0011)	(0.0014)
$DestFlights\_small$	-0.0009	0.0006	-0.0015
	(0.0013)	(0.0010)	(0.0014)
$Bankrupt\_before$	-0.0042**	0.0045**	-0.0087**
	(0.0013)	(0.0011)	(0.0014)
$Bankrupt$	-0.0026*	-0.0013	-0.0013
	(0.0012)	(0.0008)	(0.0012)
$Bankrupt\_after$	0.0064**	0.0119**	-0.0055**
	(0.0015)	(0.0012)	(0.0015)
$HR5900\_shortrun$	0.0191**	0.0030**	0.0161**
	(0.0007)	(0.0003)	(0.0007)
$HR5900\_longrun$	-0.0065**	-0.0014**	-0.0051**
	(0.0007)	(0.0005)	(0.0008)
N	508,942	508,942	508,942

Note: The dependent variable in the regression results reported in Columns (1), (2), and (3) are $Delay15$, $Delay15\_Control$, and $Delay15\_Diff$, respectively. Carrier-route fixed effects and carrier-month fixed effects suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

In order to determine the statistical significance of the differences between the coefficients in Columns (1) and (2), we turn our attention to Column (3) in Table 5, which reports the regression results using $Delay15\_Diff$ as the dependent variable. Note that the coefficients in Columns (1) and (2) generate the coefficients in Column (3). For example, the coefficient for $HR5900\_shortrun$ in Column (3) of Table 5 is 0.0161. This is the difference between traditional treatment delays ($Delay15$) and traditional control delays ($Delay15\_Control$) in the short run: $0.0191 - 0.0030 =$

0.0161. In other words, the difference between traditional treatment delays and traditional control delays in the long run fell by 161 basis points compared to this gap in our baseline time period, the three years between the approval of the H.R. 5900 legislation and its effective date. Again, this suggests a stronger long run decline in on-time performance in terms of traditional treatment delays compared to traditional control delays.

Figure 3 provides an event study plot of the $YearMonth\tau$ time dummies using $Delay15\_Diff$ as the dependent variable in Equation (1). In other words, we illustrate the estimated coefficients for these 60 time dummies along with their 95% confidence interval. Consistent with the results in Table 5, traditional treatment delays increased by more than traditional control delays in the short run with 21 of the 24 estimated dummies are positive and statistically significant.[18]

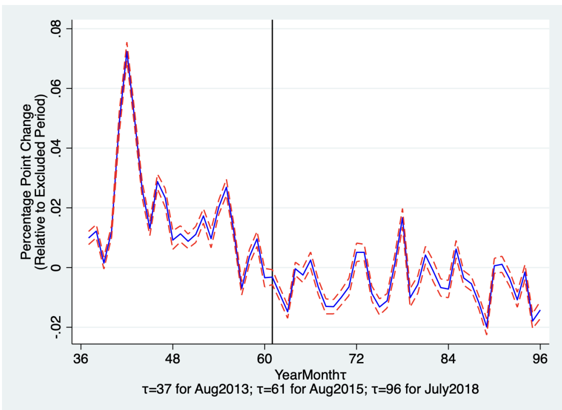


Figure 3: Treatment Delays vs. Control Delays

In a similar fashion, Table 6 analyzes extended treatment delays (i.e. extended delays due to the pilot or airline) compared to extended control delays (i.e. extended delays that are unrelated to the H.R. 5900 legislation). Once again, Column (3) in Table 6 is constructed as the difference between Columns (1) and (2). Although Equation (2) is used to estimate the $HR5900\_shortrun$ and $HR5900\_longrun$ time dummies in Table 6, Figure 4 plots the estimated coefficients and the 95% confidence intervals for the $MonthYear\tau$ time dummies using $Delay180\_Diff$ as the dependent variable in Equation (1). As with Table 5, the estimated coefficients for $HR5900\_shortrun$ are

[18]Regression results used to plot Figure 3 are reported in in Table A2, which can be found in the appendix of this paper.

positive in Table 6, which not only indicate an increase in extended treatment delays (Column (1)) and extended control delays (Column (2)), but also the difference (Column (3)) is positive so that H.R. 5900 exacerbated extended treatment delays more severely than extended control delays. As with Table 5, Column (3) in Table 6 also tests the statistical significance of these differences. For example, the Column (3) coefficient value for $HR5900\_shortrun$ is 0.0003, which suggests that the difference between extended treatment delays and extended control delays rose by 0.03 percentage points in the short run compared to our baseline time period. Figure 4 confirms this trend since a majority of the estimated time dummies are positive and statistically significant.[19] In sum, this analysis reaffirms our findings in Section 3.3 that both measures of product quality (15+ minute arrival delays and 180+ minute arrival delays) worsens immediately following the H.R. 5900 legislation.

Table 6: Extended Treatment Delays vs. Extended Control Delays

	(1) $Delay180$	(2) $Delay180\_Control$	(3) $Delay180\_Diff$
$OriginFlights\_small$	-0.0003*	-0.0006**	0.0004*
	(0.0001)	(0.0001)	(0.0002)
$DestFlights\_small$	-0.0008**	-0.0004**	-0.0004*
	(0.0002)	(0.0001)	(0.0002)
$Bankrupt\_before$	-0.0008**	0.0000	-0.0009**
	(0.0001)	(0.0001)	(0.0002)
$Bankrupt$	0.0001	-0.0003**	0.0004**
	(0.0001)	(0.0001)	(0.0001)
$Bankrupt\_after$	-0.0000	0.0002*	-0.0003
	(0.0001)	(0.0001)	(0.0002)
$HR5900\_shortrun$	0.0007**	0.0004**	0.0003**
	(0.0000)	(0.0000)	(0.0001)
$HR5900\_longrun$	0.0015**	0.0007**	0.0008**
	(0.0001)	(0.0000)	(0.0001)
N	508,942	508,942	508,942

Note: The dependent variable in the regression results reported in Columns (1), (2), and (3) are $Delay180$, $Delay180\_Control$, and $Delay180\_Diff$, respectively. Carrier-route fixed effects and carrier-month fixed effects suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

[19] 13 of the 24 time dummies in Column (3) of Table A3 in the Appendix are positive and statistically significant.

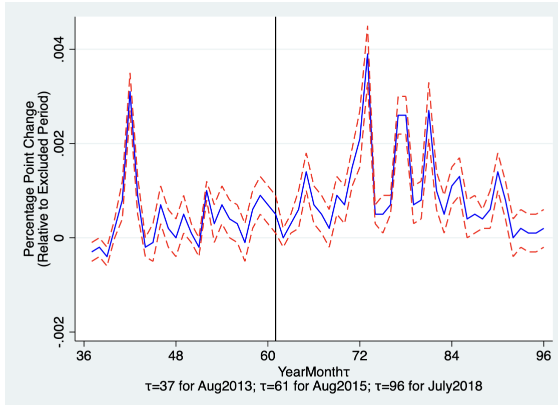
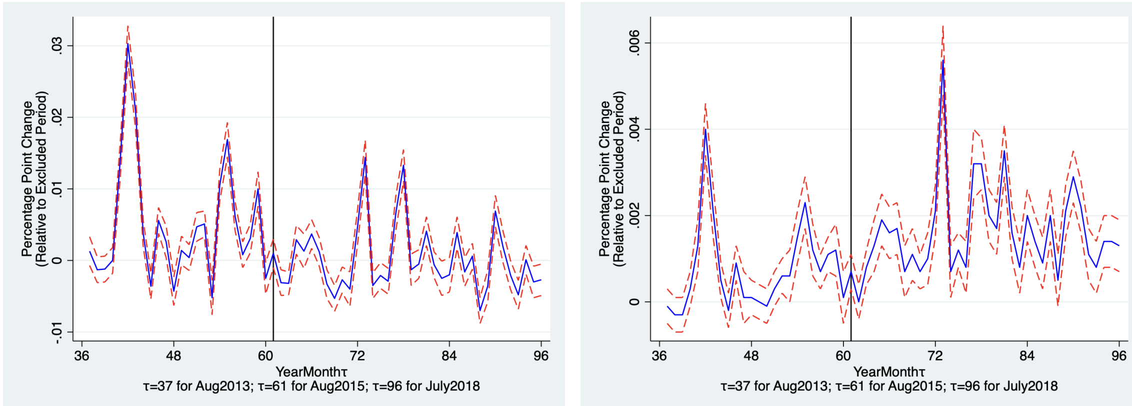


Figure 4: Extended Treatment Delays vs. Extended Control Delays

3.5 Right Start Flights

Since extended delays could be caused by the propagation of flight delays earlier in the day, we turn our attention to early morning flights in which an extended delay can be primarily attributed to either rest restrictions or weather. In particular, American Airlines refers to flights with a scheduled departure between 5:00AM and 9:00AM as "Right Start" flights. Since the aircraft should arrive at the departure airport the night before and maintenance issues can be taken care of overnight, these early morning flights are less likely to be affected by the cascading effect of flight delays. In order to analyze the effect of H.R. 5900 on Right Start flights, we keep flights in the raw data with an early morning scheduled departure time (5:00AM - 9:00AM) and aggregate these observations to the airline-route-year-month level. We re-estimate Equations (1) and (2) using this Right Start sample as a robustness check to the results presented in Sections 3.3 and 3.4. The number of observations in the Right Start sample is now less than the observations reported in Table 3 since not all airlines service every route with early morning flights.

We start by examining whether standard delays and extended delays are affected by Right Start flights. As a robustness check to Figure 2, Figure 5 illustrates a positive and statistically significant increase in the short run for both standard delays and extended delays. Table A4 in the Appendix reports that 12 of the 24 short run time dummies for both standard delays and extended delays are positive and statistically significant. This trend is confirmed when aggregating the time periods into a short run and long run time dummies in Table 7.



(a) Standard Delays (15+ Minutes) (b) Extended Delays (180+ Minutes)

Figure 5: The Effect of H.R. 5900 on On-Time Performance for Right Start Flights

Table 7: The Effect of H.R. 5900 on On-Time Performance for Right Start Flights

	(1) Standard Delays	(2) Extended Delays
$OriginFlights\_small$	0.0024	-0.0015
	(0.0055)	(0.0010)
$DestFlights\_small$	-0.0027	-0.0016
	(0.0034)	(0.0008)
$Bankrupt\_before$	-0.0036**	-0.0004
	(0.0012)	(0.0003)
$Bankrupt$	-0.0055**	0.0005*
	(0.0012)	(0.0002)
$Bankrupt\_after$	-0.0005	0.0007*
	(0.0012)	(0.0003)
$HR5900\_shortrun$	0.0041**	0.0007**
	(0.0004)	(0.0001)
$HR5900\_longrun$	-0.0000	0.0016**
	(0.0004)	(0.0001)
N	508,942	508,942

Note: This data sample consists of observations in the raw data for flights with a scheduled departure between 5:00AM and 9:00AM (Right Start flights) and then have been aggregated to the airline-route-year-month level. $Delay15$, the industry standard definition for a delayed flight (arrival at least 15 minutes late), is the dependent variable in Column (1), whereas $Delay180$, the EU's definition for an extended flight delay (arrival at least 180 minutes late), is the dependent variable in Column (2). Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

According to airline operational staff, Right Start flights set up flight crews and operations for optimal on-time performance. As such, delays for Right Start flights are most likely due to pilot rest restrictions. Therefore, it is unsurprising that Column (2) in Table 7 shows that the estimated coefficients for the short run and long run time dummies are positive and statistically significant. Since extended delays of Right Start flights most likely occur due to binding work schedule restrictions rather than the cascading effect of previously delayed flights, this analysis supports the finding in Section 3.3 that extended delays due to increased employee rest requirements have become more prevalent as a result of H.R. 5900.

Table 8 and Figure 6 present the estimated coefficients for the analysis of extended treatment delays (i.e. extended delays due to the pilot or airline) compared to extended control delays (i.e. delays due to weather, national air system, or security issues) using the Right Start subsample. As previously mentioned, extended treatment delays for Right Start flights are primarily due to binding work schedule restrictions; however, extended control delays of early morning departures are typically due to inclement weather such as fog reducing visibility below legal minimums or overnight snow accumulation. Using a similar estimation strategy as in Section 3.4, the results in Column (3) can be calculated as the difference between the regression estimates in Column (1) and Column (2). Consistent with Table 6, the positive and significant coefficient for $HR5900\_shortrun$ in Column (3) suggests that the incidence of extended treatment delays due to rest restrictions increased compared to the incidence of extended control delays due to severe weather conditions.

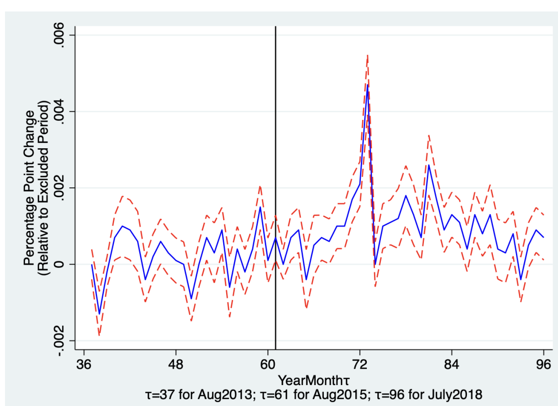


Figure 6: Extended Treatment Delays vs. Extended Control Delays for Right Start Flights

Table 8: Extended Treatment Delays vs. Extended Control Delays for Right Start Flights

	(1) $Delay180$	(2) $Delay180\_Control$	(3) $Delay180\_Diff$
$OriginFlights\_small$	-0.0015	0.0035**	-0.0050**
	(0.0010)	(0.0006)	(0.0012)
$DestFlights\_small$	-0.0016	-0.0003	-0.0013
	(0.0008)	(0.0004)	(0.0009)
$Bankrupt\_before$	-0.0004	-0.0001	-0.0003
	(0.0003)	(0.0002)	(0.0003)
$Bankrupt$	0.0005*	-0.0008**	0.0013**
	(0.0002)	(0.0001)	(0.0003)
$Bankrupt\_after$	0.0007*	-0.0000	0.0007*
	(0.0003)	(0.0002)	(0.0003)
$HR5900\_shortrun$	0.0007**	0.0005**	0.0002*
	(0.0001)	(0.0000)	(0.0001)
$HR5900\_longrun$	0.0016**	0.0006**	0.0010**
	(0.0001)	(0.0000)	(0.0001)
N	267,787	267,787	267,787

Note: This data sample consists of observations in the raw data for flights with a scheduled departure between 5:00AM and 9:00AM (Right Start flights) and then have been aggregated to the airline-route-year-month level. The dependent variable in the regression results reported in Columns (1), (2), and (3) are $Delay180$, $Delay180\_Control$, and $Delay180\_Diff$, respectively. Carrier-route fixed effects and carrier-month fixed effects suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

In sum, these results highlight the multi-dimensionality of product quality in the airline industry. The H.R. 5900 legislation was designed to improve U.S. airline safety and on this metric quality has improved. There are additional quality measures beyond safety which have also been affected by this legislation. We find that both standard flight delays and extended flight delays in have become more prevalent in the two years after H.R. 5900 legislation went into effect.

4 Conclusion

The primary objective of the H.R. 5900 legislation was to improve the safety of U.S. airline transportation and this objective appears to have been achieved given that no fatal accidents due to pilot error have occurred in the U.S. since the crash of Colgan Air flight 3407 in February 2009. This legislation which increased the occupational licensing requirements to obtain an air transport pilot license and mandated stricter scheduling restrictions for all pilots, however, had unintended consequences on product quality and pilot productivity.

While most prior research on occupational licensing (Kleiner, 2006; Kleiner, 2013; Kleiner and Kurdle, 2000; Kleiner et al., 2016) has shown stricter occupational licensing standards have no measurable impact on product quality, we find significant changes have occurred in aviation product quality. More specifically, using the U.S. aviation industry standard definition of flight delay (arrivals 15+ minutes late), we find evidence that H.R. 5900 led to worse on-time performance in the short run. We attribute this reduction in quality to shirking pilots who are behaving opportunistically given the subsequent pilot shortage. Comparing treatment delays with control delays unaffected by H.R. 5900 confirm that these results are not being driven by a secular trend in on-time performance in the airline industry.

An alternative explanation or competing hypothesis exists to our opportunistic pilot behavior narrative can be used to explain the short run increase observed in standard delays after the HR5900 legislation goes into effect. Table 2 in Section 2 shows a steady increase in the number of newly issued Airmen Certificates rising from 3,072 in 2010 to 8,346 in 2013. The implications from this rapid increase in the number of Airmen Certificates is a bubble of inexperienced airline transport pilots. These new pilots likely needed more time to go through the pre-flight checklist and other procedures prior to departure which could lead to an increase in standard delays. As these pilots gain experience, they are able to complete pre-flight tasks quicker; hence, the issue with standard flight delays is resolved in the long run. In sum, H.R. 5900 remains the trigger which led to the increase in short run standard flight delays under this competing hypothesis, however, it is not the opportunistic behavior of experienced pilots who are working more slowly but the rapid rise of inexperienced pilots operating aircraft that require more time to complete pre-flight tasks.

Another key finding is that when using the European Union's definition of an extended flight delay (arrivals 180+ minutes late) as a measure of product quality, we find product quality has gotten worse for extended delays in both the short run and long run. These lengthy delays do not reflect pilot effort, but instead may be due to a tight pilot labor market where airlines have difficulty finding replacement flight crews following a schedule disruption. Hence, airlines may lack having sufficient qualified replacement crews that can fill in at the last minute for pilots that have reached maximum duty time limits. A consequence of the pilot shortage is that flight schedules can be quite fragile. In other words, a minor schedule disruption which previously caused a short delay can now lead to an extended delay.

Airlines have been actively trying to rectify the pilot shortage. For example, American Airlines has tried to poach pilots from cargo companies with lucrative signing bonuses,[20] whereas Spirit Airlines has partnered with flight schools to fast track prospective pilots.[21] Since it can take several years for someone to reach the 1,500 hour mark as stipulated in H.R. 5900, airlines have continued to experience logistical challenges in obtaining adequate staffing of airline transport pilots since this legislation went into effect.

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Appendix A Regression Tables Used for Figures

Table A1: The Effect of H.R. 5900 on On-Time Performance

	(1) Standard Delays	(2) Extended Delays
OriginFlights_small	0.0231**	0.0002
	(0.0015)	(0.0002)
DestFlights_small	0.0051**	-0.0004*
	(0.0015)	(0.0002)
Bankrupt_before	-0.0065**	-0.0009**
	(0.0013)	(0.0001)
Bankrupt	-0.0037**	0.0002
	(0.0012)	(0.0001)
Bankrupt_after	-0.0088**	-0.0005**
	(0.0017)	(0.0001)
Aug2013	0.0133**	-0.0008**
	(0.0011)	(0.0001)
Sept2013	0.0070**	0.0007**
	(0.0012)	(0.0001)
Oct2013	-0.0013	-0.0009**
	(0.0009)	(0.0001)
Nov2013	0.0114**	0.0004**
	(0.0009)	(0.0001)
Dec2013	0.0661**	0.0017**
	(0.0017)	(0.0002)
Jan2014	0.0861**	0.0064**
	(0.0015)	(0.0002)
Feb2014	0.0645**	0.0029**
	(0.0012)	(0.0002)
Mar2014	0.0251**	-0.0003*
	(0.0012)	(0.0001)
Apr2014	0.0096**	-0.0006**
	(0.0011)	(0.0001)
May2014	0.0284**	0.0014**
	(0.0011)	(0.0001)
June2014	0.0344**	0.0003
	(0.0015)	(0.0002)
July2014	0.0044**	-0.0005**
	(0.0016)	(0.0002)
Aug2014	0.0183**	0.0009**
	(0.0013)	(0.0002)
Sept2014	0.0163**	0.0007**
	(0.0011)	(0.0001)
Oct2014	0.0220**	0.0006**
	(0.0012)	(0.0001)
Nov2014	0.0285**	0.0013**
	(0.0010)	(0.0001)
Dec2014	0.0187**	0.0004*
	(0.0016)	(0.0002)
Jan2015	0.0260**	0.0013**
	(0.0011)	(0.0001)
Feb2015	0.0431**	0.0023**
	(0.0013)	(0.0002)
Mar2015	0.0094**	0.0007**
	(0.0011)	(0.0001)
Apr2015	-0.0121**	-0.0002
	(0.0010)	(0.0001)
May2015	-0.0014	0.0009**
	(0.0011)	(0.0001)
June2015	0.0107**	0.0011**
	(0.0012)	(0.0002)
July2015	-0.0139**	-0.0008**
	(0.0015)	(0.0002)

	(1) Continued	(2) Continued
Aug2015	-0.0049**	0.0005**
	(0.0011)	(0.0001)
Sept2015	-0.0193**	-0.0000
	(0.0010)	(0.0001)
Oct2015	-0.0271**	0.0002
	(0.0009)	(0.0001)
Nov2015	0.0019*	0.0018**
	(0.0009)	(0.0001)
Dec2015	-0.0038**	0.0029**
	(0.0011)	(0.0002)
Jan2016	-0.0038**	0.0010**
	(0.0012)	(0.0002)
Feb2016	-0.0144**	0.0023**
	(0.0011)	(0.0002)
Mar2016	-0.0116**	0.0004**
	(0.0011)	(0.0002)
Apr2016	-0.0274**	0.0000
	(0.0010)	(0.0001)
May2016	-0.0195**	-0.0001
	(0.0010)	(0.0001)
June2016	-0.0101**	0.0007**
	(0.0014)	(0.0002)
July2016	0.0040**	0.0040**
	(0.0015)	(0.0002)
Aug2016	0.0142**	0.0049**
	(0.0012)	(0.0002)
Sept2016	-0.0126**	0.0005**
	(0.0011)	(0.0001)
Oct2016	-0.0189**	0.0002
	(0.0011)	(0.0001)
Nov2016	-0.0128**	0.0006**
	(0.0009)	(0.0001)
Dec2016	0.0103**	0.0041**
	(0.0013)	(0.0002)
Jan2017	0.0335**	0.0046**
	(0.0014)	(0.0002)
Feb2017	-0.0108**	0.0014**
	(0.0014)	(0.0002)
Mar2017	-0.0026*	0.0014**
	(0.0012)	(0.0002)
Apr2017	0.0091**	0.0053**
	(0.0012)	(0.0002)
May2017	0.0065**	0.0015**
	(0.0015)	(0.0002)
June2017	-0.0008	0.0012**
	(0.0014)	(0.0002)
July2017	-0.0084**	0.0016**
	(0.0014)	(0.0002)
Aug2017	0.0145**	0.0018**
	(0.0015)	(0.0002)
Sept2017	-0.0130**	0.0007**
	(0.0011)	(0.0001)
Oct2017	-0.0108**	0.0013**
	(0.0010)	(0.0001)
Nov2017	-0.0238**	0.0003*
	(0.0009)	(0.0001)
Dec2017	-0.0236**	0.0013**
	(0.0012)	(0.0002)
Jan2018	-0.0033**	0.0030**
	(0.0010)	(0.0002)
Feb2018	0.0058**	0.0023**
	(0.0012)	(0.0002)
Mar2018	-0.0135**	0.0002
	(0.0012)	(0.0001)
Apr2018	-0.0142**	0.0009**
	(0.0012)	(0.0002)
May2018	0.0001	0.0016**
	(0.0011)	(0.0002)
June2018	-0.0147**	0.0012**
	(0.0012)	(0.0002)
July2018	-0.0123**	0.0019**
	(0.0014)	(0.0002)
N	508,942	508,942

Note: *Delay*15, the industry standard definition for a delayed flight (arrival at least 15 minutes late), is the dependent variable in Column (1), whereas *Delay*180, the EU's definition for an extended flight delay (arrival at least 180 minutes late), is the dependent variable in Column (2). Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Table A2: Treatment Delays vs. Control Delays

	(1) $Delay15$	(2) $Delay15\_Control$	(3) $Delay15\_Diff$
$OriginFlights\_small$	0.0231**	-0.0037**	0.0268**
	(0.0015)	(0.0012)	(0.0015)
$DestFlights\_small$	0.0051**	0.0018	0.0033*
	(0.0015)	(0.0011)	(0.0016)
$Bankrupt\_before$	-0.0065**	0.0040**	-0.0105**
	(0.0013)	(0.0011)	(0.0014)
$Bankrupt$	-0.0037**	-0.0013	-0.0024
	(0.0012)	(0.0009)	(0.0013)
$Bankrupt\_after$	-0.0088**	0.0080**	-0.0168**
	(0.0017)	(0.0012)	(0.0016)
Aug2013	0.0133**	0.0034**	0.0099**
	(0.0011)	(0.0006)	(0.0011)
Sept2013	0.0070**	-0.0051**	0.0122**
	(0.0012)	(0.0007)	(0.0011)
Oct2013	-0.0013	-0.0028**	0.0015
	(0.0009)	(0.0007)	(0.0010)
Nov2013	0.0114**	-0.0007	0.0121**
	(0.0009)	(0.0006)	(0.0010)
Dec2013	0.0661**	0.0177**	0.0484**
	(0.0017)	(0.0009)	(0.0019)
Jan2014	0.0861**	0.0137**	0.0724**
	(0.0015)	(0.0009)	(0.0016)
Feb2014	0.0645**	0.0146**	0.0500**
	(0.0012)	(0.0009)	(0.0014)
Mar2014	0.0251**	-0.0011	0.0261**
	(0.0012)	(0.0007)	(0.0014)
Apr2014	0.0096**	-0.0036**	0.0131**
	(0.0011)	(0.0006)	(0.0012)
May2014	0.0284**	-0.0004	0.0288**
	(0.0011)	(0.0007)	(0.0013)
June2014	0.0344**	0.0110**	0.0234**
	(0.0015)	(0.0007)	(0.0016)
July2014	0.0044**	-0.0048**	0.0092**
	(0.0016)	(0.0007)	(0.0016)
Aug2014	0.0183**	0.0071**	0.0113**
	(0.0013)	(0.0008)	(0.0014)
Sept2014	0.0163**	0.0075**	0.0088**
	(0.0011)	(0.0008)	(0.0012)
Oct2014	0.0220**	0.0109**	0.0111**
	(0.0012)	(0.0010)	(0.0014)
Nov2014	0.0285**	0.0112**	0.0173**
	(0.0010)	(0.0007)	(0.0012)
Dec2014	0.0187**	0.0090**	0.0097**
	(0.0016)	(0.0009)	(0.0016)
Jan2015	0.0260**	0.0059**	0.0202**
	(0.0011)	(0.0007)	(0.0012)
Feb2015	0.0431**	0.0162**	0.0269**
	(0.0013)	(0.0008)	(0.0014)
Mar2015	0.0094**	-0.0023**	0.0116**
	(0.0011)	(0.0008)	(0.0013)
Apr2015	-0.0121**	-0.0052**	-0.0070**
	(0.0010)	(0.0007)	(0.0011)
May2015	-0.0014	-0.0050**	0.0036**
	(0.0011)	(0.0009)	(0.0012)
June2015	0.0107**	0.0012	0.0096**
	(0.0012)	(0.0007)	(0.0013)
July2015	-0.0139**	-0.0105**	-0.0034*
	(0.0015)	(0.0009)	(0.0016)
	(1) Continued	(2) Continued	(3) Continued
Aug2015	-0.0049**	-0.0016	-0.0032*
	(0.0011)	(0.0009)	(0.0013)
Sept2015	-0.0193**	-0.0103**	-0.0090**
	(0.0010)	(0.0008)	(0.0011)
Oct2015	-0.0271**	-0.0123**	-0.0148**
	(0.0009)	(0.0008)	(0.0011)
Nov2015	0.0019*	0.0023**	-0.0004
	(0.0009)	(0.0007)	(0.0011)
Dec2015	-0.0038**	-0.0013	-0.0025
	(0.0011)	(0.0007)	(0.0013)
Jan2016	-0.0038**	-0.0063**	0.0025
	(0.0012)	(0.0009)	(0.0014)
Feb2016	-0.0144**	-0.0079**	-0.0065**
	(0.0011)	(0.0009)	(0.0013)
Mar2016	-0.0116**	0.0015	-0.0130**
	(0.0011)	(0.0009)	(0.0013)
Apr2016	-0.0274**	-0.0142**	-0.0131**
	(0.0010)	(0.0008)	(0.0012)
May2016	-0.0195**	-0.0096**	-0.0100**
	(0.0010)	(0.0008)	(0.0013)
June2016	-0.0101**	-0.0036**	-0.0065**
	(0.0014)	(0.0009)	(0.0015)
July2016	0.0040**	-0.0011	0.0051**
	(0.0015)	(0.0009)	(0.0016)
Aug2016	0.0142**	0.0091**	0.0051**
	(0.0012)	(0.0009)	(0.0014)
Sept2016	-0.0126**	-0.0039**	-0.0087**
	(0.0011)	(0.0008)	(0.0013)
Oct2016	-0.0189**	-0.0057**	-0.0132**
	(0.0011)	(0.0010)	(0.0014)
Nov2016	-0.0128**	-0.0016	-0.0111**
	(0.0009)	(0.0009)	(0.0012)
Dec2016	0.0103**	0.0090**	0.0013
	(0.0013)	(0.0011)	(0.0016)
Jan2017	0.0335**	0.0168**	0.0167**
	(0.0014)	(0.0011)	(0.0016)
Feb2017	-0.0108**	-0.0007	-0.0101**
	(0.0014)	(0.0013)	(0.0016)
Mar2017	-0.0026*	0.0032**	-0.0057**
	(0.0012)	(0.0010)	(0.0015)
Apr2017	0.0091**	0.0049**	0.0042**
	(0.0012)	(0.0011)	(0.0015)
May2017	0.0065**	0.0075**	-0.0011
	(0.0015)	(0.0013)	(0.0018)
June2017	-0.0008	0.0058**	-0.0067**
	(0.0014)	(0.0008)	(0.0015)
July2017	-0.0084**	-0.0012	-0.0072**
	(0.0014)	(0.0008)	(0.0015)
Aug2017	0.0145**	0.0083**	0.0062**
	(0.0015)	(0.0009)	(0.0015)
Sept2017	-0.0130**	-0.0095**	-0.0035**
	(0.0011)	(0.0008)	(0.0012)
Oct2017	-0.0108**	-0.0054**	-0.0054**
	(0.0010)	(0.0008)	(0.0012)
Nov2017	-0.0238**	-0.0119**	-0.0119**
	(0.0009)	(0.0007)	(0.0011)
Dec2017	-0.0236**	-0.0036**	-0.0199**
	(0.0012)	(0.0009)	(0.0014)
Jan2018	-0.0033**	-0.0039**	0.0006
	(0.0010)	(0.0008)	(0.0013)
Feb2018	0.0058**	0.0047**	0.0011
	(0.0012)	(0.0010)	(0.0014)
Mar2018	-0.0135**	-0.0097**	-0.0038**
	(0.0012)	(0.0008)	(0.0013)
Apr2018	-0.0142**	-0.0034**	-0.0108**
	(0.0012)	(0.0007)	(0.0013)
May2018	0.0001	0.0016	-0.0015
	(0.0011)	(0.0008)	(0.0013)
June2018	-0.0147**	0.0032**	-0.0179**
	(0.0012)	(0.0007)	(0.0013)
July2018	-0.0123**	0.0019*	-0.0142**
	(0.0014)	(0.0008)	(0.0015)
N	508,942	508,942	508,942

Note: The dependent variable in the regression results reported in Columns (1), (2), and (3) are $Delay15$, $Delay15\_Control$, and $Delay15\_Diff$, respectively. Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Table A3: Extended Treatment Delays vs. Extended Control Delays

	(1) $Delay180$	(2) $Delay180\_Control$	(3) $Delay180\_Diff$
$OriginFlights\_small$	0.0002	-0.0008**	0.0010**
	(0.0002)	(0.0001)	(0.0002)
$DestFlights\_small$	-0.0004*	-0.0006**	0.0002
	(0.0002)	(0.0001)	(0.0002)
$Bankrupt\_before$	-0.0009**	0.0000	-0.0009**
	(0.0001)	(0.0001)	(0.0002)
$Bankrupt$	0.0002	-0.0002*	0.0004**
	(0.0001)	(0.0001)	(0.0002)
$Bankrupt\_after$	-0.0005**	0.0000	-0.0005**
	(0.0001)	(0.0001)	(0.0002)
Aug2013	-0.0008**	-0.0005**	-0.0003*
	(0.0001)	(0.0001)	(0.0001)
Sept2013	0.0007**	0.0009**	-0.0002
	(0.0001)	(0.0001)	(0.0001)
Oct2013	-0.0009**	-0.0004**	-0.0004**
	(0.0001)	(0.0001)	(0.0001)
Nov2013	0.0004**	0.0003**	0.0002
	(0.0001)	(0.0001)	(0.0001)
Dec2013	0.0017**	0.0009**	0.0008**
	(0.0002)	(0.0001)	(0.0002)
Jan2014	0.0064**	0.0033**	0.0031**
	(0.0002)	(0.0002)	(0.0002)
Feb2014	0.0029**	0.0019**	0.0009**
	(0.0002)	(0.0001)	(0.0002)
Mar2014	-0.0003*	-0.0001	-0.0002
	(0.0001)	(0.0001)	(0.0001)
Apr2014	-0.0006**	-0.0005**	-0.0001
	(0.0001)	(0.0001)	(0.0002)
May2014	0.0014**	0.0008**	0.0007**
	(0.0001)	(0.0001)	(0.0002)
June2014	0.0003	0.0001	0.0002
	(0.0002)	(0.0001)	(0.0002)
July2014	-0.0005**	-0.0005**	-0.0000
	(0.0002)	(0.0001)	(0.0002)
Aug2014	0.0009**	0.0003**	0.0005**
	(0.0002)	(0.0001)	(0.0002)
Sept2014	0.0007**	0.0006**	0.0001
	(0.0001)	(0.0001)	(0.0001)
Oct2014	0.0006**	0.0008**	-0.0002
	(0.0001)	(0.0001)	(0.0001)
Nov2014	0.0013**	0.0003**	0.0010**
	(0.0001)	(0.0001)	(0.0001)
Dec2014	0.0004*	0.0000	0.0003
	(0.0002)	(0.0001)	(0.0002)
Jan2015	0.0013**	0.0006**	0.0007**
	(0.0001)	(0.0001)	(0.0002)
Feb2015	0.0023**	0.0019**	0.0004*
	(0.0002)	(0.0001)	(0.0002)
Mar2015	0.0007**	0.0004**	0.0003
	(0.0001)	(0.0001)	(0.0002)
Apr2015	-0.0002	-0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0002)
May2015	0.0009**	0.0002*	0.0006**
	(0.0001)	(0.0001)	(0.0002)
June2015	0.0011**	0.0001	0.0009**
	(0.0002)	(0.0001)	(0.0002)
July2015	-0.0008**	-0.0015**	0.0007**
	(0.0002)	(0.0001)	(0.0002)
	(1) Continued	(2) Continued	(3) Continued
Aug2015	0.0005**	-0.0000	0.0005**
	(0.0001)	(0.0001)	(0.0002)
Sept2015	-0.0000	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)
Oct2015	0.0002	-0.0001	0.0003*
	(0.0001)	(0.0001)	(0.0001)
Nov2015	0.0018**	0.0012**	0.0006**
	(0.0001)	(0.0001)	(0.0002)
Dec2015	0.0029**	0.0014**	0.0014**
	(0.0002)	(0.0001)	(0.0002)
Jan2016	0.0010**	0.0002*	0.0007**
	(0.0002)	(0.0001)	(0.0002)
Feb2016	0.0023**	0.0018**	0.0005*
	(0.0002)	(0.0001)	(0.0002)
Mar2016	0.0004**	0.0002*	0.0002
	(0.0002)	(0.0001)	(0.0002)
Apr2016	0.0000	-0.0009**	0.0009**
	(0.0001)	(0.0001)	(0.0002)
May2016	-0.0001	-0.0008**	0.0007**
	(0.0001)	(0.0001)	(0.0002)
June2016	0.0007**	-0.0008**	0.0015**
	(0.0002)	(0.0001)	(0.0002)
July2016	0.0040**	0.0019**	0.0021**
	(0.0002)	(0.0002)	(0.0003)
Aug2016	0.0049**	0.0009**	0.0039**
	(0.0002)	(0.0001)	(0.0003)
Sept2016	0.0005**	0.0001	0.0005**
	(0.0001)	(0.0001)	(0.0001)
Oct2016	0.0002	-0.0002**	0.0005**
	(0.0001)	(0.0001)	(0.0002)
Nov2016	0.0006**	-0.0001	0.0007**
	(0.0001)	(0.0001)	(0.0001)
Dec2016	0.0041**	0.0015**	0.0026**
	(0.0002)	(0.0001)	(0.0002)
Jan2017	0.0046**	0.0020**	0.0026**
	(0.0002)	(0.0001)	(0.0002)
Feb2017	0.0014**	0.0007**	0.0007**
	(0.0002)	(0.0001)	(0.0002)
Mar2017	0.0014**	0.0006**	0.0008**
	(0.0002)	(0.0001)	(0.0002)
Apr2017	0.0053**	0.0026**	0.0027**
	(0.0002)	(0.0002)	(0.0003)
May2017	0.0015**	0.0005**	0.0010**
	(0.0002)	(0.0002)	(0.0002)
June2017	0.0012**	0.0007**	0.0005*
	(0.0002)	(0.0001)	(0.0002)
July2017	0.0016**	0.0006**	0.0011**
	(0.0002)	(0.0001)	(0.0002)
Aug2017	0.0018**	0.0005**	0.0013**
	(0.0002)	(0.0001)	(0.0002)
Sept2017	0.0007**	0.0003**	0.0004**
	(0.0001)	(0.0001)	(0.0002)
Oct2017	0.0013**	0.0008**	0.0005**
	(0.0001)	(0.0001)	(0.0002)
Nov2017	0.0003*	-0.0002*	0.0004**
	(0.0001)	(0.0001)	(0.0001)
Dec2017	0.0013**	0.0008**	0.0006**
	(0.0002)	(0.0001)	(0.0002)
Jan2018	0.0030**	0.0016**	0.0014**
	(0.0002)	(0.0001)	(0.0002)
Feb2018	0.0023**	0.0015**	0.0008**
	(0.0002)	(0.0001)	(0.0002)
Mar2018	0.0002	0.0002*	-0.0000
	(0.0001)	(0.0001)	(0.0002)
Apr2018	0.0009**	0.0007**	0.0002
	(0.0002)	(0.0001)	(0.0002)
May2018	0.0016**	0.0015**	0.0001
	(0.0002)	(0.0001)	(0.0002)
June2018	0.0012**	0.0011**	0.0001
	(0.0002)	(0.0001)	(0.0002)
July2018	0.0019**	0.0017**	0.0002
	(0.0002)	(0.0001)	(0.0002)
N	508,942	508,942	508,942

Note: The dependent variable in the regression results reported in Columns (1), (2), and (3) are $Delay180$, $Delay180\_Control$, and $Delay180\_Diff$, respectively. Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Table A4: The Effect of H.R. 5900 on On-Time Performance for Right Start Flights

	(1) Standard Delays	(2) Extended Delays
OriginFlights_small	0.0134*	-0.0001
	(0.0058)	(0.0011)
DestFlights_small	0.0052	-0.0004
	(0.0037)	(0.0009)
Bankrupt_before	-0.0034**	-0.0003
	(0.0013)	(0.0003)
Bankrupt	-0.0047**	0.0007**
	(0.0012)	(0.0002)
Bankrupt_after	-0.0025*	0.0006*
	(0.0012)	(0.0003)
Aug2013	0.0013	-0.0001
	(0.0010)	(0.0002)
Sept2013	-0.0013	-0.0003
	(0.0009)	(0.0002)
Oct2013	-0.0012	-0.0003
	(0.0009)	(0.0002)
Nov2013	-0.0000	0.0003
	(0.0009)	(0.0002)
Dec2013	0.0140**	0.0013**
	(0.0013)	(0.0003)
Jan2014	0.0303**	0.0040**
	(0.0013)	(0.0003)
Feb2014	0.0209**	0.0021**
	(0.0012)	(0.0003)
Mar2014	0.0038**	0.0005
	(0.0009)	(0.0002)
Apr2014	-0.0036**	-0.0002
	(0.0009)	(0.0002)
May2014	0.0056**	0.0009**
	(0.0009)	(0.0002)
June2014	0.0026*	0.0001
	(0.0011)	(0.0003)
July2014	-0.0043**	0.0001
	(0.0010)	(0.0002)
Aug2014	0.0014	0.0000
	(0.0010)	(0.0002)
Sept2014	0.0004	-0.0001
	(0.0009)	(0.0002)
Oct2014	0.0047**	0.0003
	(0.0010)	(0.0002)
Nov2014	0.0051**	0.0006*
	(0.0009)	(0.0002)
Dec2014	-0.0052**	0.0006*
	(0.0012)	(0.0003)
Jan2015	0.0105**	0.0015**
	(0.0011)	(0.0003)
Feb2015	0.0169**	0.0023**
	(0.0012)	(0.0003)
Mar2015	0.0062**	0.0012**
	(0.0010)	(0.0003)
Apr2015	0.0008	0.0007**
	(0.0009)	(0.0002)
May2015	0.0031**	0.0011**
	(0.0010)	(0.0002)
June2015	0.0100**	0.0012**
	(0.0012)	(0.0003)
July2015	-0.0025*	0.0001
	(0.0011)	(0.0003)

	(1) Continued	(2) Continued
Aug2015	0.0010	0.0007**
	(0.0010)	(0.0002)
Sept2015	-0.0031**	-0.0000
	(0.0009)	(0.0002)
Oct2015	-0.0032**	0.0008**
	(0.0008)	(0.0002)
Nov2015	0.0029**	0.0013**
	(0.0010)	(0.0003)
Dec2015	0.0013	0.0019**
	(0.0012)	(0.0003)
Jan2016	0.0037**	0.0016**
	(0.0010)	(0.0003)
Feb2016	0.0012	0.0017**
	(0.0010)	(0.0003)
Mar2016	-0.0033**	0.0007**
	(0.0010)	(0.0003)
Apr2016	-0.0053**	0.0011**
	(0.0009)	(0.0003)
May2016	-0.0027**	0.0007**
	(0.0009)	(0.0002)
June2016	-0.0040**	0.0010**
	(0.0012)	(0.0003)
July2016	0.0047**	0.0021**
	(0.0012)	(0.0003)
Aug2016	0.0144**	0.0056**
	(0.0012)	(0.0004)
Sept2016	-0.0035**	0.0007*
	(0.0009)	(0.0003)
Oct2016	-0.0021*	0.0012**
	(0.0009)	(0.0002)
Nov2016	-0.0029**	0.0008**
	(0.0009)	(0.0003)
Dec2016	0.0066**	0.0032**
	(0.0012)	(0.0004)
Jan2017	0.0133**	0.0032**
	(0.0011)	(0.0003)
Feb2017	-0.0013	0.0020**
	(0.0011)	(0.0003)
Mar2017	-0.0005	0.0017**
	(0.0010)	(0.0003)
Apr2017	0.0041**	0.0035**
	(0.0010)	(0.0003)
May2017	-0.0006	0.0016**
	(0.0009)	(0.0003)
June2017	-0.0025*	0.0008**
	(0.0012)	(0.0003)
July2017	-0.0020	0.0020**
	(0.0012)	(0.0003)
Aug2017	0.0039**	0.0014**
	(0.0011)	(0.0003)
Sept2017	-0.0016	0.0009**
	(0.0010)	(0.0003)
Oct2017	0.0006	0.0020**
	(0.0009)	(0.0003)
Nov2017	-0.0070**	0.0005
	(0.0009)	(0.0003)
Dec2017	-0.0036**	0.0021**
	(0.0011)	(0.0003)
Jan2018	0.0069**	0.0029**
	(0.0011)	(0.0003)
Feb2018	0.0019	0.0022**
	(0.0011)	(0.0003)
Mar2018	-0.0021*	0.0011**
	(0.0010)	(0.0003)
Apr2018	-0.0048**	0.0008**
	(0.0010)	(0.0003)
May2018	0.0001	0.0014**
	(0.0010)	(0.0003)
June2018	-0.0030**	0.0014**
	(0.0011)	(0.0003)
July2018	-0.0027*	0.0013**
	(0.0011)	(0.0003)
N	267,787	267,787

Note: This data sample consists of observations in the raw data for flights with a scheduled departure between 5:00AM and 9:00AM (Right Start flights) and then have been aggregated to the airline-route-year-month level. *Delay*15, the industry standard definition for a delayed flight (arrival at least 15 minutes late), is the dependent variable in Column (1), whereas *Delay*180, the EU's definition for an extended flight delay (arrival at least 180 minutes late), is the dependent variable in Column (2). Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.

Table A5: Extended Treatment Delays vs. Extended Control Delays for Right Start Flights

	(1)	(2)	(3)
	$Delay180$	$Delay180\_Control$	$Delay180\_Diff$
$OriginFlights\_small$	-0.0001	0.0027**	-0.0028*
	(0.0011)	(0.0006)	(0.0012)
$DestFlights\_small$	-0.0004	-0.0010*	0.0006
	(0.0009)	(0.0005)	(0.0010)
$Bankrupt\_before$	-0.0003	0.0000	-0.0003
	(0.0003)	(0.0002)	(0.0003)
$Bankrupt$	0.0007**	-0.0006**	0.0013**
	(0.0002)	(0.0001)	(0.0003)
$Bankrupt\_after$	0.0006*	0.0000	0.0006
	(0.0003)	(0.0002)	(0.0003)
Aug2013	-0.0001	-0.0001	0.0000
	(0.0002)	(0.0001)	(0.0002)
Sept2013	-0.0003	0.0010**	-0.0013**
	(0.0002)	(0.0001)	(0.0003)
Oct2013	-0.0003	-0.0001	-0.0002
	(0.0002)	(0.0001)	(0.0002)
Nov2013	0.0003	-0.0003**	0.0007**
	(0.0002)	(0.0001)	(0.0003)
Dec2013	0.0013**	0.0004	0.0010**
	(0.0003)	(0.0002)	(0.0004)
Jan2014	0.0040**	0.0031**	0.0009*
	(0.0003)	(0.0003)	(0.0004)
Feb2014	0.0021**	0.0016**	0.0006
	(0.0003)	(0.0002)	(0.0004)
Mar2014	0.0005	0.0009**	-0.0004
	(0.0002)	(0.0002)	(0.0003)
Apr2014	-0.0002	-0.0004**	0.0002
	(0.0002)	(0.0001)	(0.0003)
May2014	0.0009**	0.0003*	0.0006*
	(0.0002)	(0.0001)	(0.0003)
June2014	0.0001	-0.0002	0.0003
	(0.0003)	(0.0002)	(0.0003)
July2014	0.0001	0.0000	0.0001
	(0.0002)	(0.0001)	(0.0003)
Aug2014	0.0000	0.0001	-0.0000
	(0.0002)	(0.0001)	(0.0003)
Sept2014	-0.0001	0.0008**	-0.0009**
	(0.0002)	(0.0001)	(0.0003)
Oct2014	0.0003	0.0002	0.0000
	(0.0002)	(0.0001)	(0.0003)
Nov2014	0.0006*	-0.0001	0.0007*
	(0.0002)	(0.0002)	(0.0003)
Dec2014	0.0006*	0.0003	0.0003
	(0.0003)	(0.0002)	(0.0004)
Jan2015	0.0015**	0.0006**	0.0009**
	(0.0003)	(0.0002)	(0.0003)
Feb2015	0.0023**	0.0029**	-0.0006
	(0.0003)	(0.0003)	(0.0004)
Mar2015	0.0012**	0.0008**	0.0004
	(0.0003)	(0.0002)	(0.0003)
Apr2015	0.0007**	0.0008**	-0.0002
	(0.0002)	(0.0002)	(0.0003)
May2015	0.0011**	0.0007**	0.0004
	(0.0002)	(0.0002)	(0.0003)
June2015	0.0012**	-0.0003*	0.0015**
	(0.0003)	(0.0001)	(0.0003)
July2015	0.0001	0.0000	0.0001
	(0.0003)	(0.0001)	(0.0003)

	(1)	(2)	(3)
	Continued	Continued	Continued
Aug2015	0.0007**	0.0000	0.0007**
	(0.0002)	(0.0001)	(0.0003)
Sept2015	-0.0000	-0.0000	0.0000
	(0.0002)	(0.0001)	(0.0002)
Oct2015	0.0008**	0.0001	0.0007**
	(0.0002)	(0.0001)	(0.0003)
Nov2015	0.0013**	0.0005**	0.0009**
	(0.0003)	(0.0002)	(0.0003)
Dec2015	0.0019**	0.0023**	-0.0004
	(0.0003)	(0.0002)	(0.0004)
Jan2016	0.0016**	0.0010**	0.0005
	(0.0003)	(0.0002)	(0.0004)
Feb2016	0.0017**	0.0010**	0.0007*
	(0.0003)	(0.0002)	(0.0003)
Mar2016	0.0007**	0.0001	0.0006
	(0.0003)	(0.0001)	(0.0003)
Apr2016	0.0011**	0.0001	0.0010**
	(0.0003)	(0.0001)	(0.0003)
May2016	0.0007**	-0.0003*	0.0010**
	(0.0002)	(0.0001)	(0.0003)
June2016	0.0010**	-0.0008**	0.0017**
	(0.0003)	(0.0001)	(0.0003)
July2016	0.0021**	-0.0000	0.0021**
	(0.0003)	(0.0001)	(0.0003)
Aug2016	0.0056**	0.0010**	0.0047**
	(0.0004)	(0.0001)	(0.0004)
Sept2016	0.0007*	0.0007**	-0.0000
	(0.0003)	(0.0001)	(0.0003)
Oct2016	0.0012**	0.0001	0.0010**
	(0.0002)	(0.0001)	(0.0003)
Nov2016	0.0008**	-0.0003*	0.0011**
	(0.0003)	(0.0001)	(0.0003)
Dec2016	0.0032**	0.0020**	0.0012**
	(0.0004)	(0.0002)	(0.0004)
Jan2017	0.0032**	0.0015**	0.0018**
	(0.0003)	(0.0002)	(0.0004)
Feb2017	0.0020**	0.0007**	0.0013**
	(0.0003)	(0.0002)	(0.0004)
Mar2017	0.0017**	0.0010**	0.0007*
	(0.0003)	(0.0002)	(0.0003)
Apr2017	0.0035**	0.0010**	0.0026**
	(0.0003)	(0.0002)	(0.0004)
May2017	0.0016**	-0.0000	0.0017**
	(0.0003)	(0.0001)	(0.0003)
June2017	0.0008**	-0.0001	0.0009**
	(0.0003)	(0.0002)	(0.0003)
July2017	0.0020**	0.0007**	0.0013**
	(0.0003)	(0.0001)	(0.0003)
Aug2017	0.0014**	0.0003*	0.0011**
	(0.0003)	(0.0001)	(0.0003)
Sept2017	0.0009**	0.0005**	0.0004
	(0.0003)	(0.0001)	(0.0003)
Oct2017	0.0020**	0.0007**	0.0013**
	(0.0003)	(0.0002)	(0.0003)
Nov2017	0.0005	-0.0004*	0.0008**
	(0.0003)	(0.0001)	(0.0003)
Dec2017	0.0021**	0.0008**	0.0013**
	(0.0003)	(0.0002)	(0.0004)
Jan2018	0.0029**	0.0024**	0.0004
	(0.0003)	(0.0003)	(0.0004)
Feb2018	0.0022**	0.0019**	0.0003
	(0.0003)	(0.0002)	(0.0004)
Mar2018	0.0011**	0.0003	0.0008**
	(0.0003)	(0.0002)	(0.0003)
Apr2018	0.0008**	0.0012**	-0.0004
	(0.0003)	(0.0002)	(0.0003)
May2018	0.0014**	0.0009**	0.0005
	(0.0003)	(0.0002)	(0.0003)
June2018	0.0014**	0.0006**	0.0009*
	(0.0003)	(0.0002)	(0.0003)
July2018	0.0013**	0.0006**	0.0007*
	(0.0003)	(0.0002)	(0.0003)
N	267,787	267,787	267,787

Note: This data sample consists of observations in the raw data for flights with a scheduled departure between 5:00AM and 9:00AM (Right Start flights) and then have been aggregated to the airline-route-year-month level. The dependent variable in the regression results reported in Columns (1), (2), and (3) are $Delay180$, $Delay180\_Control$, and $Delay180\_Diff$, respectively. Carrier-route fixed effects and carrier-month fixed effects are suppressed. Standard errors are clustered by carrier-route and reported in parentheses. * and ** indicate statistical significance at the 5% and 1% levels, respectively.