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Did deregulation affect aircraft engine maintenance? an empirical policy analysis

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Examination of aircraft engine histories provided by Pratt & Whitney, Inc., indicates a significant increase in the number of engine hours between major overhauls in the period following deregulation. Parametric analysis of times between overhauls, which controls for other variables affecting the length of the shop visit cycle, suggests that deregulation is a significant factor in the change. Logit analysis, however, shows that engine "failures" (as measured by in-flight shutdowns) have not increased as a result of deregulation. These findings suggest that airlines have responded to competitive pressures by optimizing scheduled service times and perhaps by improving the quality of service performed but paying less attention to minor problems between scheduled shop visits.

1. Introduction

■ A major focus of popular media attention to the airline deregulation[1] issue has been on the question of aircraft safety. While economists have devoted journal space to other aspects of deregulation, safety has been a major concern in academic circles as well.

Economists agreed that deregulation would bring down the average price of airline travel, but there was less certainty surrounding the effect on quality of service. Theorists posited that during the regulated era, airlines competed in quality—since price competition was not available to them (see Douglas and Miller (1974))—and there has been theoretical treatment of the notion that deregulation would bring a reduction in quality (Moses and

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[1] For this analysis, deregulation is taken to have occurred in 1978, the year Congress passed the Airline Deregulation Act. Of course, actions taken by the Civil Aeronautics Board (CAB) before 1978 (as well as airlines' expectations) could support an argument for an earlier cutoff date, and that the Act did not abolish the CAB until 1982 could support a later cutoff date. In using 1978 as the cutoff, I am following the examples of Morrison and Winston (1988) and Borenstein and Zimmerman (1988).

Savage, 1990; Kamien and Vincent, 1990; Panzar and Savage, 1987; Stiglitz and Arnott, 1987; and Braeutigam, 1987) as well as empirical treatment of the notion that airlines have moved sharply to control costs (for example, Card (1986, 1989) on the decline of wages paid airline employees since deregulation). A key component of quality of service is aircraft safety.

There is direct evidence that aggregate safety has not declined since deregulation (see Rose (1992) and Morrison and Winston (1988)), and that airlines' safety records were not affected by profitability either before (see Golbe (1986)) or after (see Rose (1990)) deregulation. Borenstein and Zimmerman (1988) provide evidence that the reverse does not hold: airlines experiencing accidents do suffer financial losses, although not nearly at the level of the social costs.

These empirical studies share one important feature: The number of observations in which an accident is present is quite small. Statistical analysis of rare events is problematic, and it is not inconceivable that results could be driven by airlines' "lucky" or "unlucky" draws. One way of getting around this difficulty is to analyze the actions taken by airlines to enhance safety, and one such action is aircraft engine maintenance.

This article looks at two questions: Did deregulation lead airlines to reduce engine maintenance effort? And if there was a reduction in effort, has it led to deterioration in engine performance?

This study differs from previous ones in two important ways. First, this article is largely an analysis of "effort" as opposed to "performance." I measure effort by the preventive maintenance performed on aircraft engines. Engine maintenance occurs quite frequently, and because its purpose is to prevent engine failures and, hence, accidents, analysis of maintenance effort is a valid approach to the study of safety.

Second, this study employs a unique and rich dataset not previously available to researchers. Data were collected at the level of an individual aircraft engine, enabling an examination of micro-level decision making in the maintenance process. The data take the form of 42 complete engine histories covering the years 1964 to 1988 provided by Pratt & Whitney, Inc.[2] A major advantage of this dataset is the relatively large number of events to be analyzed (engine shutdowns and shop visits) compared to the infrequent occurrence of accidents and what the National Transportation Safety Board terms "incidents" analyzed in the other studies.

2. Background

■ Before describing the data, methodology, and results, it is worthwhile to discuss aircraft engines, maintenance, and regulations briefly. A mechanic described the operation of a jet engine succinctly as "suck, squeeze, bang, and blow." [3] This expression offers a fair representation of major engine processes: Air is pulled into the engine, compressed, and mixed with fuel. The explosion of this mixture and its exhaust propels the plane forward. The high temperatures and intense pressures take a heavy toll on the engine's components, and maintenance and repair can be costly (Table 1). Much of the cost is labor.

The decision to remove and overhaul an engine depends heavily on information gathered by both the pilot and the ground crew during service checks. Some critical measures, like oil pressure, are readily observable from the cockpit. The ground crew collects other data,

[2] Because I wished to address the question of how deregulation affected the treatment of individual engines, the sample was drawn from engines whose service lives covered a substantial period both before and after deregulation. I argue below that the fact that the engines are overhauled means that they are "renewed" at each shop visit and may therefore be considered new engines; this renewal puts the engines on an approximately equal footing with other renewed engines.

[3] Personal interview with Charlie Walters and Roy Fife, aircraft mechanics with Federal Express, Inc., Madison, April 9, 1988.

TABLE 1 **Maintenance Cost per Shop Visit**

Type of Visit	Cost per Visit (Thousands of Dollars) JT8D	JT9D
Full engine refurbishment	225–325	500–800
Hot section refurbishment	125–175	300–400
Miscellaneous repair	50–100	100–150

Source: Pratt & Whitney, Inc. Costs reflect parts and labor.

such as boroscope readings. In addition, the engine may encounter foreign object damage (FOD), particularly from birds or large hailstones, which may necessitate an engine removal. Finally, an engine may be removed as part of a progressive maintenance program or for engine rotation.[4]

Federal regulations govern all aircraft engine-related matters.[5] An air carrier wishing to perform service on its own aircraft must meet essentially three sets of standards. First, it must meet the standards set forth in the manufacturer's Federal Aviation Administration (FAA)-approved maintenance manuals. Second, it must meet the standards of its own FAA-approved progressive inspection and maintenance program. Finally, it must meet the additional airworthiness standards set forth in the CFR (Code of Federal Regulations), as well as the regulations concerning records, personnel, and working conditions. The air carrier has some latitude in determining its inspection and maintenance program, although once the airline has committed itself to a specific program it cannot deviate from it. Thus, if the maintenance regulations were binding before deregulation, deregulation should not have affected the airlines' standards.

Many union officials and airline employees insist that the story is more complicated, however. They allege that since the advent of deregulation the incentives to cut costs have driven airlines to hire less-qualified applicants for critical positions, including pilots and line mechanics.[6] It should be noted that these personnel must still meet the criteria set forth in the CFR; but primary sources argue that formerly there had been a great deal of slack in the constraints, whereas now there is very little margin between applicant qualifications and the minimums specified in the CFR.

When an engine fails, the consequences are unlikely to be serious, because the aircraft has at least one other engine and can readily perform an emergency landing with the remaining engine(s). Typically, a pilot experiencing an in-flight shutdown will continue to the scheduled destination, unless the shutdown occurred during or shortly after takeoff or there are no qualified mechanics at the destination. Of course, the cost of more than one engine failing on a given aircraft is self-evident and has been quantified (at least indirectly) by Borenstein and Zimmerman (1988).

Obviously, a major objective of airline engine maintenance is to minimize the chance of engine failure. To some extent, the probability of failure is outside the airline's control; a typical exogenous problem is that of FOD. However, engine shutdowns also may result from faulty maintenance or from a pilot's decision based on instrument readings in the cockpit (which sometimes turn out to be false, explaining how an engine may have more

[4] Personal correspondence with Edward R. Cowles, Public Relations Director, Pratt & Whitney, Inc.

[5] Most of the pertinent regulations are Parts 21, 33, 43, and 145 in Volume 14 of the Code of Federal Regulations (CFR).

[6] One such allegation was made in the ABC News *Nightline* television program, Show #1798, April 13, 1988, by a Continental Airlines mechanic.

than one shutdown during one shop visit cycle). The engine work in this dataset also reflects the installation of upgrade kits, designed to improve an engine's performance.

3. Preliminary analysis

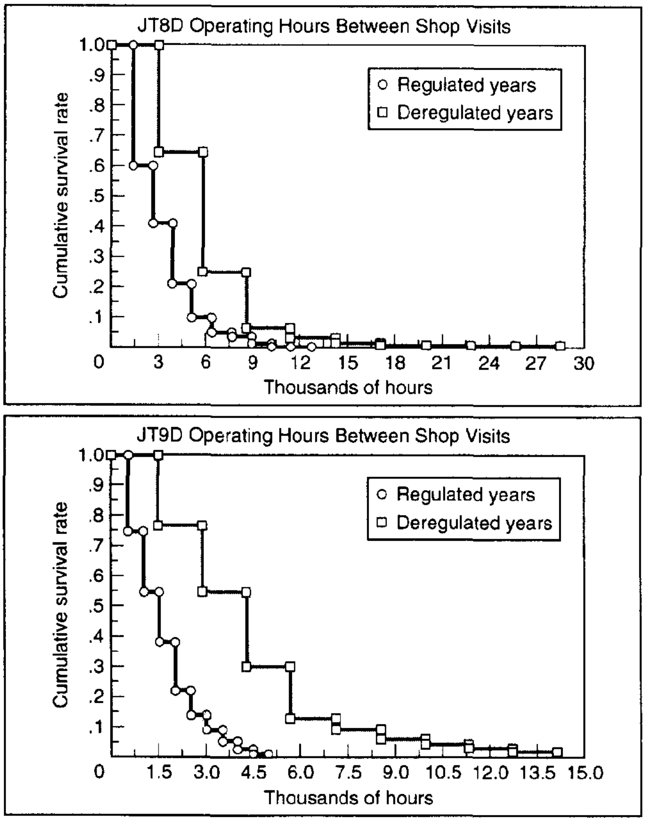
■ Survival plots (see Kalbfleisch and Prentice (1980)) in Figure 1 suggest that aircraft engines on average are allowed to remain in operation for more engine hours before being overhauled since deregulation than before.

All things equal, we might expect an airline that overhauls engines more frequently to have a better safety record than its rivals. Thus, Figure 1 might initially excite an observer's concern. Indeed, the data for both JT8D and JT9D[7] engines fail the log-rank and generalized Wilcoxon tests for homogeneity of prederegulation and postderegulation data.

We can also observe the distinction between regulated-era and deregulated-era data in the distributions of operating hours, or "hard time," between shop visits, shown in Figure 2. Engines in both categories appear to have much longer shop visit cycles on average

FIGURE 1

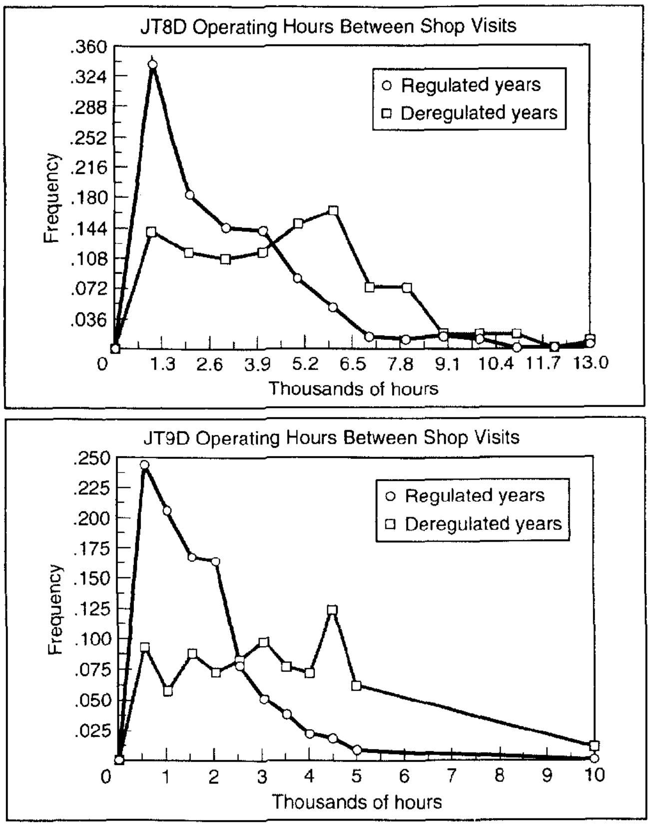
SURVIVAL FUNCTION



[7] JT8D engines have approximately 16,000 pounds of thrust and are generally the engine of choice on Boeing 727 and McDonnell-Douglas DC-9 aircraft. JT9D engines have 41,000 pounds of thrust and are often used on Boeing 747s.

FIGURE 2

FREQUENCY DISTRIBUTION



in the deregulated era. A χ^2 test on the frequencies for each jet type rejects the null hypothesis that the regulated and deregulated samples are drawn from the same distribution.[8]

Table 2 shows that the average number of operating hours between overhauls roughly doubled (from over 2,100 prederegulation to about 4,400 postderegulation) for JT8D engines and more than doubled (from about 1,300 prederegulation to about 3,500 postderegulation) for JT9D engines. A t-test reveals statistically significant differences between the means.[9] A relevant question is whether the longer shop visit cycles in the deregulated era justify concern or whether they represent improved technology's effect on engine wear and tear. Because the engine histories record each technological upgrade implemented on each engine, my dataset can answer this question.

4. Parametric analysis of shop visit cycles and shutdowns

■ **Model specification.** In this parametric analysis, I start by assuming that operating hours (t) between shop visits are distributed as two-parameter Weibull (μ_i, α), where μ and α

[8] For JT8D and JT9D engines the values of the test statistic are 228.7009 and 142.383, respectively, with associated degrees of freedom 11 and 8 and tail probabilities 1.545×10^{-9} and 7.577×10^{-27}. The formula for the test statistic is given in the Appendix.

[9] The t-statistics are 6.3789 and 10.7594 for the JT8D and JT9D engines respectively, where the alternative hypothesis is that the deregulated means are greater than the regulated (tail probabilities for both statistics are computed to be less than 10^{-4}).

TABLE 2 **Summary Statistics**

	Years Before Deregulation					Years Since Deregulation				
	Mean	Standard Deviation	Maximum	Minimum	Observations	Mean	Standard Deviation	Maximum	Minimum	Observations
Thousand hours between shop visits										
JT8D	2.149	2.177	12.714	.000	262	4.382	3.599	28.434	.002	124
JT9D	1.279	1.083	4.966	.000	314	3.473	2.702	14.129	.000	193
Months between shop visits										
JT8D	11.053	9.539	55.000	.000	262	19.411	12.655	66.000	1.000	124
JT9D	5.427	3.664	19.000	.000	314	11.580	8.402	47.000	1.000	193
Thousand hours per month between shop visits ("intensity")										
JT8D	.219	.245	3.463	.001	257	.215	.081	.810	.002	124
JT9D	.227	.107	.932	.000	305	.286	.098	.954	.004	193
Thousand hours from shop visit to first shutdown										
JT8D	2.151	1.952	7.997	.000	70	3.400	3.633	12.090	.000	10
JT9D	.736	.837	3.636	.001	110	1.762	2.135	11.985	.000	74

are, respectively, the location and scale parameters. Subscript i indexes a "renewal"—that is, a shop visit cycle. This particular parameterization of the Weibull maximum likelihood estimator is due to Lancaster (1979).

Letting t_i denote the (hard) time between shop visits $i - 1$ and i, the Weibull probability density function is given by[10]

$$f(t_i) = \mu_i \alpha t_i^{\alpha-1} \exp(-\mu_i t_i^{\alpha}) \tag{1}$$

with

$$\mu_i = \exp(\beta' x_i), \tag{2}$$

where x_i denotes the vector of covariates and β denotes the (unknown) vector of parameters.[11] The data x_i contain information on prior shutdowns, prior shop visit rates, engine upgrading, "intensity" of operation, and airline operator. Based on the dates of events, shop visit cycles are classified as occurring during the regulated era or the deregulated era (post-1978), which enables another dummy covariate for deregulation.[12] Table 3 gives the definitions, means, and standard deviations for continuous variables. The sample log-likelihood is obtained by

TABLE 3 **Variables Used**

HRSLSV	=	Thousand engine hours since last shop visit; also referred to as "hard time." Mean = (3.05, 2.18); Standard Deviation = (2.87, 2.14).
SVRT	=	Prior shop visit rate; the number of prior shop visits divided by thousands of engine hours. Mean = (5.38, 10.38); Standard Deviation = (6.57, 10.69).
DEREG	=	Deregulation dummy; 1 after January 1978, 0 before.
AL1–AL7	=	Airline indicators; there are seven airlines represented in the sample.
DC9	=	Dummy for McDonnell-Douglas DC-9 aircraft; some JT8D engines were installed on DC-9s.
SDDUM	=	Dummy to indicate the existence of a shutdown history since the last shop visit.
ELTIME	=	Elapsed time; calendar time in months since last shop visit. This time is distinguished from "hard" time, since it does not necessarily reflect hours of usage. Mean = (13.92, 7.91); Standard Deviation = (11.28, 6.61).
INTENS	=	"Intensity"; thousands of engine hours since last shop visit divided by elapsed time since last shop visit. Mean = (.21, .25); Standard Deviation = (.21, .11).
7/7A/7B *15CN* *15ACN* *17CN* *9/9A*	=	Model number dummies representing upgrades in JT8D engines.
7CN *7ACN* *7ASPCN*	=	Model number dummies representing upgrades in JT9D engines.

Note: Means and standard deviations are given in the order (JT8D engines, JT9D engines).

[10] This model is popular in unemployment duration studies; see also Heckman and Borjas (1980), Heckman and Singer (1985), and Flinn and Heckman (1982).

[11] Any function of parameters and data that guarantees a positive location parameter will work. The exponential form given in equation (2) is the function of choice for most empirical work.

[12] An alternative approach is to separate the sample into regulated years and unregulated years and analyze the differential effect of covariates on the hazards for the two periods. Results from this approach are qualitatively similar but for brevity are not reported here (they are available from the author).

taking the natural logarithm of equation (1) and summing over i for each engine; α is restricted to $\alpha > 0$ by estimating $\ln(\alpha)$.

My priors on the coefficients were as follows. If we are to believe the story of, say, Kamien and Vincent (1990) that airlines overprovided quality before deregulation, the deregulation dummy (*DEREG*) should negatively influence the hazard, since firms would have scaled back their maintenance effort in the face of fierce rivalry.

Prior shop visit rate (*SVRT*), which indicates the number of times the engine visited the shop per thousand hours of hard time prior to the current shop visit cycle, can play two roles. First, it may signal the seriousness of the airline's maintenance program: a higher shop visit rate is equivalent to more maintenance and thus will lead to a lower hazard rate. Alternatively, the shop visit rate may indicate engines with more problems requiring shop attention, in which case the effect on the hazard rate will be positive. Thus, I will not specify a prior on shop visit rate; the data are permitted to choose which of the two hypotheses applies.[13]

The shutdown dummy (*SDDUM*) should have a negative effect on the hazard rate, because this indicator conveys the information that an engine has experienced trouble of some sort during its current cycle.

Intensity of use (*INTENS*) should have a positive effect on the hazard rate, assuming that it is accurately measured, because a more intensely used engine can be expected to wear out (and therefore require shop attention) more quickly. I must note, though, that the intensity measure here is quite problematic: it simply relates hard time to elapsed time, and does not take into account (for example) takeoffs and landings, when engines undergo the greatest portion of their stress. A useful measure of the intensity of operation would have been engine "cycles," or hours of operation at full throttle; unfortunately, these were very inconsistently recorded in the dataset. Conceivably, an engine with a higher intensity under the measure I use may be one that is used on longer, but fewer, flights, and may thus affect hazard negatively.

The upgrade dummies (see Table 3) should proxy technical improvements in the engines and should thus have a negative effect on the hazard rate, since an improved engine is less likely to require service.

I will take no position on airline dummies (*AL1* to *AL7*), because I do not know the actual airlines involved and thus have no way of discovering their safety records. However, I will venture to assert that as factors leading to the deterioration of an engine are controlled for, a positive coefficient for a given airline is suggestive of a greater willingness to perform maintenance (as opposed to a response to a more problematic collection of engines). The assertion is strengthened by noting that an airline fixed effect applies to *all* engines operated by the airline, and that it is unlikely that all of an airline's engines in the sample are "lemons."

The *DC9* dummy for JT8D engines should have a positive effect on the hazard rate because the DC-9 is a two-engine underwing aircraft. The fact that there are two (versus three for the Boeing 727) suggests that the engines are stressed more. Also, mechanics indicated to me that although underwing engines are somewhat easier to service, they seem to have more maintenance problems, possibly because of wing vibration and because nothing is in front of the engines to keep out FOD.

The data suffer from neither right nor left censoring because each shop visit cycle—except for the first installation—is preceded by a shop visit and is followed by another shop visit. Thus, no correction is required. Even though a given engine goes through many cycles (of uptime, shop visit), following the example of Amemiya (1985) and others I treat the uptimes as independent events. In other words, I am assuming that an engine returning to

[13] It should be pointed out that the shop visit rate as measured here does not include contemporaneous shop visits, but only those that occurred up to the time of the last shop visit. Thus, this specification should not suffer from any problems of endogeneity.

TABLE 4 Weibull and Least Squares Results
Dependent Variable: Engine Hours Between Shop Visits

Variable	Weibull Models: JT8D Engines		Weibull Models: JT9D Engines		OLS Models: JT8D Engines		OLS Models: JT9D Engines	
Primary variables								
Constant	.379	−.954	2.233	.004	−1.430	−2.068	−.532	−.900
	(.258)	(.114)	(.186)	(.077)	(.272)	(.242)	(.158)	(.150)
	.177	−.016	1.849	1e-04				
Shop visit rate	.030	.036	.001	.001	.031	.035	1e-04	2e-04
	(.005)	(.004)	(1e-04)	(1e-04)	(.013)	(.013)	(2e-04)	(2e-04)
	.014	.001	.001	.000				
Deregulation dummy	−.307	−.298	−.398	−.534	−.986	−.911	−1.432	−1.304
	(.158)	(.140)	(.185)	(.185)	(.347)	(.356)	(.322)	(.332)
	−.136	−.005	−.317	−.013				
Shutdown dummy	−.386	−.282	−.200	−.176	−1.035	−.937	−.287	−.277
	(.240)	(.220)	(.164)	(.152)	(.546)	(.560)	(.288)	(.297)
	−.152	−.004	−.153	−.004				
Intensity	−6.771		−11.801		−3.004		−2.051	
	(1.259)		(.963)		(.645)		(.348)	
	−3.156		−9.77					
Engine upgrade dummies								
7/7A/7B	−.476	−.579			−1.119	−1.212		
	(.146)	(.133)			(.309)	(.316)		
	−.222	−.010						
15CN	−.580	−.642			−1.450	−1.558		
	(.244)	(.209)			(.549)	(.564)		
	−.217	−.009						
15ACN	−.529	−.460			−.907	−.984		
	(.492)	(.290)			(1.103)	(1.133)		
	−.193	−.006						
17CN	−.724	−.800			−1.142	−1.365		
	(.430)	(.408)			(.952)	(.977)		
	−.246	−.010						
9/9A	−.862	−3.023			−24.528	−25.839		
	(1.161)	(1.054)			(2.469)	(2.520)		
	−.270	−.017						
7CN			−.292	−.606			−.720	−.750
			(.133)	(.128)			(.230)	(.238)
			−.226	−.013				
7ACN			−.261	−.820			−.912	−1.156
			(.198)	(.197)			(.343)	(.352)
			−.209	−.019				
7ASPCN			−.351	−1.143			−2.034	−2.379
			(.504)	(.489)			(.874)	(.902)
			−.246	−.017				
Airline dummies								
AL2	−.188	−.100	.080	−.236	−.685	−.538	.118	−.346
	(.196)	(.187)	(.212)	(.198)	(.430)	(.441)	(.375)	(.379)
	.081	−.002	.069	−.005				
AL3	−.260	−.350	−.134	−.218	−.429	−.510	−.284	−.324
	(.240)	(.230)	(.157)	(.118)	(.540)	(.554)	(.278)	(.287)
	−.109	−.005	−.105	−.005				
AL4	−.534	−.510	−.130	−.210	−1.332	−1.289	−.524	−.533
	(.317)	(.200)	(.163)	(.134)	(.620)	(.636)	(.289)	(.299)
	−.197	−.007	−.102	−.005				

TABLE 4 *Continued*

Variable	Weibull Models				OLS Models			
	JT8D Engines		JT9D Engines		JT8D Engines		JT9D Engines	
AL5	.146 (.243) .073	.568 (.262) .013			.876 (.621)	1.218 (.634)		
AL6	−.049 (.277) −.022	−.015 (.108) −2e-04			−.343 (.593)	−.369 (.609)		
AL7	.131 (.259) .065	.147 (.237) .003			.338 (.549)	.418 (.564)		
DC9	.311 (.237) .163	.522 (.216) .011			.754 (.512)	.978 (.523)		
α	1.240 (.053)	1.160 (.050)	1.346 (.050)	1.107 (.043)	—	—	—	—
−Log-likelihood	738.2	762.1	732.8	814.7	856.2	867.2	1006.0	1023.0
R-squared	—	—	—	—	.395	.359	.317	.269
F statistic	—	—	—	—	15.047	13.829	22.980	20.287
Degrees of freedom	368	369	495	496	369	370	496	497

Notes: Standard errors in parentheses. Weibull hazard derivatives under standard errors. OLS results relate to the negative of duration to facilitate comparison.

service from the shop is essentially a new engine, having been certified as meeting airworthiness standards.[14]

□ **Estimation results.** Parameter estimates derived from a Weibull maximum likelihood approach are efficient if in fact the data-generating process is Weibull. If the process is not Weibull, estimates are not consistent. For this reason, I have also estimated parameters by ordinary least squares (OLS), for which at least the claim can be made that estimates provide the best linear predictor. Diagnostics of the specifications tested are discussed later.

Because the Weibull specification allows for duration dependence (if $\alpha \neq 1$), the influence of the explanatory variables changes over time.[15] To facilitate interpretation, I computed the value of the derivative of the Weibull hazard function, $h(\mu, \alpha) = \mu\alpha t^{\alpha-1}$, with respect to each variable, evaluated at the mean of the variables. In the case of binary explanatory variables, I use $h(\mu(X^j, 1, \beta), \alpha) - h(\mu(X^j, 0, \beta), \alpha)$, where X^j is the mean of the data matrix containing all columns except the binary variable in the jth position; the second argument of μ is the assumed value of the binary variable in the jth column.

Table 4 gives Weibull and OLS results for JT8D and JT9D engines. Because OLS results provide the best linear predictor (see, for example, Goldberger (1991)) of the dependent variable given the covariates, they serve as a basis for comparison for the more restrictive Weibull model. Diagnostics for both specifications are discussed below.

[14] This assumption is not completely innocuous, because the FAA has sets of standards for "new," "reconditioned," and "airworthy" engines. However, the data do not allow me to distinguish between servicings that truly regenerate the engine to the "new" status and those that merely render the engine "airworthy." The ramification is that engines repaired to airworthy standards may have somewhat shorter expected service lives than those repaired to reconditioned standards.

[15] If α were to equal one, the model reduces to an exponential distribution of operation times and would indicate a true Markov process (see equation (1)). In that case, coefficients can be interpreted directly as derivatives of the response variable with respect to the independent variables.

Deregulation is distinguishable as a separate effect negatively influencing the shop visit hazard rate in the Weibull specification and significantly increasing the length of the shop visit cycle in the OLS specification.[16] The result stands for both engines at the 10% significance level whether or not the intensity measure is included.

Table 2 shows that while the intensity measure rose significantly since deregulation for JT9D engines, it has not changed significantly for JT8D engines.[17] Because the intensity ratio is a less-than-perfect proxy, I also report Weibull results with the intensity measure not present in Table 4. The data, however, reject this restriction.[18]

Table 4 reveals that intensity has both positive and significant effects on the Weibull hazard rates for both engine types. That result seems to indicate that as intensity of use increases (operating hours per month increase), the likelihood of an engine requiring a shop visit increases. OLS estimates of the intensity coefficient are significant as well. The data seem to support the hypothesis that the more intensively used engines are employed on longer trips and have relatively fewer takeoffs and landings.

Prior shop visit rate has a positive and significant effect on the hazard rate for both engine types. That result most likely comes about because engines with weaker prior histories tend to break down more easily. This explanation is consistent with the OLS results for JT8D but not JT9D engines.

Engine upgrade packages had negative and significant effects on the Weibull hazard in the *7/7A/7B, 15CN,* and *17CN* cases for JT8D engines and in the case of *7CN* for JT9D engines. That is to say, these particular upgrade packages led to increased service lives for the engines on which they were installed. When intensity is excluded, upgrade packages except Model 15ACN exhibit statistically significant effects relative to Model 1/1A/1B (the original JT8D model); the statistically significant coefficients all reflect reductions in the hazard rate. All the engine updates applied to the JT9D engines reduce the hazard rate relative to Model 3A, the original JT9D model, when intensity is excluded. OLS results are slightly different: in the JT8D case, *7/7A/7B, 15CN,* and *9/9A* have significant coefficients, while in the JT9D case, all three upgrades appear to have significant coefficients.

Only airline 4 (*AL4*) in the JT8D case has significant (negative) effects on the Weibull shop visit hazard when intensity is included. Without intensity, airlines 4 and 5 are significant for JT8D engines (negatively and positively, respectively, with respect to the hazard rate). It follows based on the earlier reasoning that airline 4 is less safety-conscious than its peers, and airline 5 more so. If the intensity measure is excluded, only airline 3 behaves significantly differently—it seems to be less safety-conscious. The OLS results are roughly consistent with the Weibull for JT8D engines; airlines 4 and 5 have significant coefficients with the signs consistent with the Weibull results. The JT9D OLS results show a significant effect for airline 4.

The JT9D engines were installed on only one aircraft type, the Boeing 747, so no aircraft dummy was included. The JT8D engines in the sample were installed on both Boeing 727 and Douglas DC-9 aircraft. The Weibull results indicate that the fact that a given engine is installed on a DC-9 had a positive and significant effect on the hazard rate when intensity is excluded, but no significant effect when intensity is included. The DC-9 effect is significant in both OLS specifications. This result may reflect more intense usage when the JT8Ds are installed on the DC-9, which is a two-engine aircraft as opposed to the three-engine 727.

[16] Because Weibull estimates refer to the influence on the hazard, I report the negative of estimated OLS coefficients in Table 4 to make the coefficients comparable across the two models.

[17] The *t*-statistic for the difference in mean "intensity" for JT8D engines is .236, while that for JT9Ds is 6.315.

[18] The likelihood ratio for the JT8D engines is 47.8 (χ^2 distribution tail probability is 1.5×10^{-9}), and that for JT9D engines is 163.8 (tail probability also 1.5×10^{-9}).

TABLE 5 Binary Logit Results
Monthly Probability of Engine Shutdown

Variable	JT8D Engines Model 1	JT8D Engines Model 2	JT9D Engines Model 1	JT9D Engines Model 2
Primary variables				
Constant	−2.7127 (.2955)	−3.2132 (.1958)	−1.9048 (.2002)	−2.1193 (.1314)
Hours since last shop visit	.0214 (.0610)	.0595 (.0572)	−.0695 (.0450)	−.0614 (.0444)
Prior shop visit rate	−.1037 (.0499)		−.1065 (.0125)	
Deregulation dummy	−.7837 (.4099)	−.7426 (.4096)	−.0650 (.3114)	−.0448 (.3107)
Engine upgrade dummies				
7/7A/7B	−1.2087 (.2790)	−1.1872 (.2773)		
15CN	−2.7130 (1.0760)	−2.7542 (1.0760)		
15ACN	−.8216 (1.0968)	−.8212 (1.0966)		
17CN	−13.6910 (236.7088)	−22.2733 (289.5752)		
9/9A	−13.2838 (424.5485)	−22.3762 (629.1351)		
7CN			−.3270 (.2031)	−.2704 (.2005)
7ACN			−.8585 (.3257)	−.7893 (.3224)
7ASPCN			−2.0166 (1.0623)	−1.9375 (1.0618)
Airline dummies				
AL2	−.1707 (.4847)	−.3480 (.4762)	−.8491 (.3728)	−.7859 (.3706)
AL3	−1.1148 (.5585)	−.9771 (.5570)	−.1561 (.2347)	−.0951 (.2309)
AL4	−.7484 (.5361)	−.8016 (.5354)	−1.6759 (.4578)	−1.6860 (.4579)
AL5	−.2821 (1.0465)	−.7203 (1.0275)		
AL6	.4846 (.4490)	.3331 (.4408)		
AL7	−.8823 (.7286)	−.7514 (.7264)		
DC9	.2782 (.5127)	.2210 (.5110)		
−Log-likelihood	378.22	380.68	825.57	826.78
Degrees of freedom	5372	5373	4091	4092

Note: Standard errors in parentheses.

For both engine types, the results indicate an increasing hazard rate ($\alpha > 1$), and at a significance level of 10% or less.[19] That result reflects the essence of preventive maintenance, which will cause an engine to eventually be called into the shop after enough operating hours have passed even if the engine is within airworthiness minimums.

Whether the engine experienced one or more shutdowns (indicated by the shutdown dummy) during the time of operation had no significant effect on the process. This result is somewhat counterintuitive and may reflect that random factors in the shutdown process prevail over maintenance-related factors. I have accordingly estimated a logit model that purports to explain engine shutdowns, to be discussed below.

As we can observe in Table 2, the average number of operating hours from a shop visit to the first engine shutdown has increased for both engine types since the regulated era. Once again, we are confronted with the question of whether this change is caused by the covariates observable in the data or whether deregulation has had an influence.

Table 5 gives binary logit results for monthly in-flight shutdowns as a function of a constant, hours since last shop visit, shop visit rate, deregulation dummy, and airline and engine model dummies. Although the number of shutdowns per operating hour would seem to have gone down (because the number of hours from engine removal to first shutdown has increased), the deregulation coefficient is negative and significant only for the JT8Ds and insignificant for the JT9Ds. These results suggest that the increased length of the shop visit cycle after deregulation has at least not led to a decline in reliability for these engines, when in-flight shutdowns are the proxy for (the inverse of) reliability.

I considered the possibility that because shop visit rate has declined since deregulation, the correlation between the two variables makes the estimates less precise.[20] Thus, I re-estimated excluding the shop visit rate. Table 5 shows that coefficient estimates are fairly stable (with the exception of the *17CN* and *9/9A* dummies, which are a very small fraction of the dataset), but the qualitative results on deregulation remain the same: it led to a significant decline in the likelihood of engine shutdown for JT8D engines and has a statistically insignificant but negative effect for JT9D engines. Although data are not available for other potential reliability indicators, such as average exhaust pressure ratios, exhaust gas temperature readings, and boroscope results, the evidence seems to suggest that engine reliability has either remained constant or improved since deregulation. This result seems even more compelling if we note that, as Table 2 shows, intensity of use (or at least hours of operation per month) have increased in the same period.

Both engine types have strongly significant constants, due to the large random component in engine shutdowns (events beyond the operators' control). Surprisingly, neither engine type shows a significant effect for hours since last shop visit.[21] However, in the case of JT8Ds, higher shop visit rates significantly decrease the probability of a shutdown.

□ **Model diagnostics.** D'Agostino, Belanger, and D'Agostino (1990) describe the D'Agostino-Pearson omnibus test procedure for detecting deviations from normality based on sample skewness and kurtosis. The OLS models presented in Table 4 strongly reject normality.[22,23] I performed the Box-Cox transformation (BC) on the dependent variable, hours of operation between shop visits, where

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[19] Since I estimated ln (α) rather than α itself, the standard errors for α are computed using the delta method (see Billingsley (1979)).

[20] Although it might at first appear that the shop visit rate and hours since last shop visit coefficients may suffer from endogeneity bias, in fact this is not so, because the data at time t are computed from the engine's *history* at time t up to but not including the current period.

[21] This result is *not* due to correlation between shop visit rate and hours since last shop visit; correlation coefficients are $-.19$ and $-.05$ for JT8D and JT9D engines, respectively.

[22] The test statistics are 63.08 and 247.09 for the JT8D and JT9D regressions, respectively (tail probabilities are both less than 10^{-4}).

[23] Vuong (1989) has proposed a model selection criterion for nonnested models that is a variation on a

$$BC(x;\Theta) = \begin{cases} \dfrac{x^{\Theta}-1}{\Theta} & \Theta \neq 0 \\ \ln(x), & \Theta = 0 \end{cases}.$$

Performing a grid search for the Θ that maximizes the log-likelihood of the sample under the assumption of normality did not alter the significance of the D'Agostino-Pearson statistic.[24] Thus the OLS results, while lending credence to the results because the technique does provide the best linear predictor, cannot be regarded as efficient estimates.

Lancaster (1979) noted that the inclusion of more explanatory variables in his model caused the value of α to rise. That observation is consistent with my finding for both engine types, and quite possibly the conclusion that he draws—heterogeneity caused by omitted variables may be responsible for the nonconstant hazard rate—may apply. Lancaster (1990) provides tests for unobserved heterogeneity and a nonmonotone hazard. The models do not seem to suffer from unobserved heterogeneity;[25] however, there is strong rejection of the monotone hazard specification.[26]

One way to address the nonmonotone hazard problem parametrically is to estimate a generalized gamma model, which fits an additional shape parameter. The generalized gamma log-likelihood is

$$L = \sum_{i=1}^{N} \{\ln(\alpha) + m\beta'x_i + (\alpha m - 1)\ln(y_i) - y_i^{\alpha}e^{\beta'x_i} - \ln(\Gamma(m))\},$$

where m is the additional shape parameter (note that if $m = 1$, the model is identical to the Weibull). Results from this specification are reported in Table 6; the results reject the null hypothesis that $m = 1$, and the likelihood ratio test rejects a restriction of setting m to unity. Other results are qualitatively similar to the Weibull and OLS results.

A possible specification error in the logit model is unobserved heterogeneity.[27] There appears to be no omnibus specification test for unobserved heterogeneity in the logit framework, so I considered a possible source arising from the engines themselves. The likelihood ratio test did not reject the null hypothesis that the coefficients of the engine fixed effects are all zero for both JT8D and JT9D engines.[28]

5. Conclusion

■ The dataset containing complete Pratt & Whitney aircraft engine histories exhibits a clear distinction between maintenance behavior before and after airline deregulation. An

likelihood ratio test. The formula for the test statistic in this case is given in the Appendix. The data overwhelmingly reject the null hypothesis that the Weibull and OLS models are equivalent in favor of the Weibull being better. The Vuong statistic for the unrestricted (intensity included as a covariate) JT8D model is 4.958, with associated significance 3.6×10^{-7}. The Vuong statistic for the unrestricted JT9D model is 4.459, with associated significance 4.1×10^{-6}. For the restricted case, Vuong statistic values are 6.403 and 7.211, both with significance 7.7×10^{-7}, for JT8D and JT9D models, respectively.

[24] "Optimal" Box-Cox parameters ranged from .2077 to .3375 for the four specifications in Table 4; D'Agostino-Pearson statistics ranged from 28.43 to 60.21, with associated tail probabilities less than 10^{-4}.

[25] The normally distributed, right-tailed test statistic is −4.0024 (tail probability .9999) for JT8D engines and −9.4716 (tail probability 1.0000) for JT9D engines.

[26] Test statistic values for JT8D and JT9D models are 496.1399 and 4051.5056, respectively, with associated tail probabilities both less than 10^{-4}.

[27] Another potential problem is heteroskedasticity. Davidson and MacKinnon (1984) proposed a heteroskedasticity test for a probit model in which the heteroskedasticity arises in the underlying (normal) latent variable model. However, as Greene (1990) points out (and the authors also suggest), their test does not apply to a logit framework because the logit model is not derived from a latent variable framework (except in the special case of random utility models).

[28] The likelihood ratio test statistics for the JT8D and JT9D engines are 25.67 and 10.59, respectively, with associated tail probabilities .1771 and .9562. Degrees of freedom in both cases are 20.

TABLE 6 Generalized Gamma Results
Dependent Variable: Engine Hours Between Shop Visits

Variable	JT8D Engines	JT9D Engines
Primary variables		
Constant	−.5601 (.6122) −.0565	3.5312 (.4627) .0751
Shop visit rate	.0608 (.0112) .0061	.0018 (.0003) 3.7*e*-5
Deregulation dummy	−.4551 (.2539) −.0538	−1.0612 (.4137) −.0439
Shutdown dummy	−.7703 (.4145) −.1295	−.7043 (.3257) −.0587
Intensity	−16.2541 (3.3783) −1.6392	−29.7467 (3.5222) −.6326
Engine upgrades		
7/7A/7B	−.9186 (.2672) −.0874	
15CN	−1.0267 (.4350) −.1816	
15ACN	−.8450 (.8200) −.1514	
17CN	−1.4990 (.7328) −.3202	
9/9A	−.1132 (2.0380) −.0129	
7CN		−.5440 (.2660) −.0276
Engine upgrades (continued)		
7ACN		−.4913 (.4152) −.0176
7ASPCN		−.0902 (.9381) −.0029
Airline dummies		
AL2	−.5489 (.3427) −.0815	.3908 (.3983) −.0105
AL3	−.5572 (.4082) −.0828	.1653 (.3187) .0005
AL4	−.8388 (.4787) −.1468	.0413 (.3140) .0007
AL5	−.2253 (.4856) −.0280	
AL6	.0824 (.4504) .0075	
AL7	.6506 (.4415) .0071	
DC9	.7434 (.4066) .0122	
α	2.5661 (.3430)	3.2195 (.3274)
m	.3474 (.0626)	.2820 (.0379)
−Log-likelihood	723.21	685.75
Degrees of freedom	367	494

Notes: Standard errors in parentheses. Hazard derivatives under standard errors.

OLS regression equation as well as a form of one of the standard-duration models used to capture the effects of other covariates suggests that deregulation is a significant factor in predicting the length of an engine's shop visit cycle. A logit analysis to predict the probability of an engine shutdown uses the same covariates but suggests that deregulation does not affect that likelihood.

There is support for mechanics' claims that the decline in quantifiable maintenance is a result of deregulation in the airlines. After controlling for improvements signalled by model upgrades in the engines, heterogeneity in airline maintenance practices, unobserved airline heterogeneity, heterogeneity in aircraft types, and the incidence of shutdowns, deregulation seems to have resulted in a lower probability that an engine gets a shop visit. This finding is robust to inclusion of usage intensity as an explanatory variable; however, the intensity variable is a noisy signal that may not adequately proxy the desired effect. Despite the increased time between engine overhauls, there is no evidence of reduced engine reliability as measured by in-flight shutdowns, suggesting that the counterarguments of airline managers may also be correct: safety performance has not suffered since the advent of deregulation. These results verify machinists' union claims that maintenance policies have substantially changed in the deregulated environment, but also back corporate claims that reliability has not suffered.

One way of reconciling these conflicting views is to recognize that quite possibly, new maintenance policies are at variance with the older notions of good maintenance practice—thereby leading to the unions' discomfort—but are in fact optimal from the safety standpoint. Some empirical support for this interpretation is found in Kennet (1988), where an estimated structural model (based on Rust (1987)) incorporating a dynamic programming model of maintenance decision making into a statistical model suggests that maintenance prior to 1978 was not dynamically optimized but was optimal after 1978.

The results strengthen existing literature on air safety in the deregulated environment, which has unanimously found little cause for concern, but provide the extra reassurance that comes from microdata at the level of the decision makers.

Appendix

■ The χ^2 statistic in footnote 8 is computed by determining the expected frequency for each of k ranges of values under the null hypothesis that the regulated-era distribution would apply to the deregulated era, E_j, and inserting the observed frequencies, O_j, from the deregulated era in the following formula (Kenkel, 1989):

$$\chi^2 = \sum_{j=1}^{k} \frac{(O_j - E_j)^2}{E_j}.$$

Degrees of freedom are then $k - 1$.

The test statistic for footnote 23 is $V(l_{\hat{\Theta}}^w, l_{\hat{\gamma}}^g) = n^{-1/2}(\sum_{i=1}^{n} l_i^w(\hat{\Theta}) - \sum_{i=1}^{n} l_i^g(\hat{\gamma}))/\hat{\omega}$, where $l_{\hat{\Theta}}^w$ is the vector of observation log-likelihoods evaluated under the Weibull likelihood function assumption at $\hat{\Theta}$, the associated maximum likelihood estimator for the model; $l_{\hat{\gamma}}^g$ is the vector of observation log-likelihoods evaluated under the competing Gaussian normal functional assumption at $\hat{\gamma}$, its associated maximum likelihood estimator; n is the number of observations; $l_i^w(\cdot)$ and $l_i^g(\cdot)$ are observation log-likelihoods, and

$$\hat{\omega}^2 = \frac{1}{n}\sum_{i=1}^{n}\{l_i^w(\hat{\Theta}) - l_i^g(\hat{\gamma})\}^2 - \left\{\frac{1}{n}\sum_{i=1}^{n}[l_i^w(\hat{\Theta}) - l_i^g(\hat{\gamma})]\right\}^2.$$

Vuong (1989) shows that this statistic is asymptotically standard normally distributed.

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