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Relationship of Air Traffic Control Specialist Age to En Route Operational Errors

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16. Abstract

Public Law 92-297, passed in 1971, requires that air traffic control specialists (ATCSs) hired after May 16, 1972 retire at age 56. The underlying rationale was that as controllers aged, the cumulative effects of stress, fatigue (from shift work), and age-related cognitive changes created a safety risk (U.S. House of Representatives, 1971). This hypothesis has been considered in two recent studies of en route operational errors (OEs). The Center for Naval Analyses (CNA, 1995) found no relationship between controller age and OEs. Broach (1999) reported that the probability of involvement in an OE increased with age. The purpose of this study was to re-examine the hypothesis that controller age, controlling for experience, was related to OEs. En route OE records (3,054) were matched with non-supervisory ATCS staffing records for the period FY1997-2003. Poisson regression was used to model OE count as a function of the explanatory variables age and experience using the SPSS® version 11.5 General Loglinear (GENLOG) procedure. Overall, the Poisson regression model fit the data poorly (Likelihood Ratio 2 = 283.81, p < .001). The Generalized Log Odds Ratio was used to estimate the odds ratio for age. The odds of OE involvement for older controllers (GE age 56) were 1.02 times greater than the odds for younger (LE age 55) controllers, with a 95% confidence interval of 0.42 to 1.64. This range of odds indicated that neither age group was less or more likely than the other to be involved in an OE, controlling for experience. The analysis does not support the hypothesis that older controllers are at greater risk of involvement in an OE. These results suggest that the original rationale for the mandatory retirement of controllers may need to be re-examined. Additional research on age and ATCS performance is recommended.

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INTRODUCTION

Background

In 1971, the United States Congress amended Section 8335 of Title 5 of the United States Code to require the mandatory separation of an air traffic controller at age 56 (Public Law 92-297). The law was justified in testimony on the basis of two arguments: (a) that the cumulative stress of the job and shift work would result in "burnout" for the controller, thereby increasing risks to the safety of flight; and (b) that controllers lost proficiency with age, thereby increasing risks to the safety of flight. The testimony of Donald Francke, Executive Director of the Air Traffic Control Association (ATCA) in 1971 drew a straight line between controller age and safety:

> There must be an orderly phasing out of the older controllers when they can no longer make the rapid and accurate decisions essential to the preservation of human life. This calls for recognition of the highly important fact that early retirement is not solely a matter of fairness to the controller, it is primarily a safety measure. (U.S. House of Representatives, 1971, p. 98).

The primary evidence offered for these arguments were anecdotal reports of stress from controllers, self-reported "stress-related" symptoms, physiological correlates of stress, and medical disability retirements of controllers. Despite the strong assertion made by Mr. Francke, no testimony or data were presented in 1971 to demonstrate that older controllers were more likely to make errors that might compromise the safety of flight. This study, therefore, was designed to test the hypothesis implicit in Francke's testimony that older controllers were more likely than younger controllers to commit errors that reduced the safety of flight.

Previous Research

Air traffic controllers ensure the safe, orderly, and expeditious flow of air traffic through the U.S. National Airspace System (NAS). To ensure the safety of flight, controllers maintain adequate separation between aircraft and obstacles to flight. They issue speed, altitude, and heading commands to pilots to provide and maintain required separation. An operational error (OE) results when an Air Traffic Control Specialist (ATCS, referred to in this paper as"air traffic controller," or "controller") fails to maintain appropriate separation between aircraft, terrain, and other obstacles to safe flight. OEs are rare compared with the number of operations handled in the U.S. air traffic system. For example, there were 1,145 OEs in fiscal year (FY) 2000 compared to 166,669,557 operations, or 6.8 OEs per million operations (Pounds & Ferrante, 2003; Department of Transportation Office of the Inspector General [DOT OIG, 2003a]). Despite their rarity, OEs may pose safety risks, depending on the degree to which separation is lost and are critical safety indicators for the operation of the air traffic control system (DOT OIG, 2003a,b).

As part of its strategy to enhance the safety of the nation's air traffic system, the Federal Aviation Administration (FAA) has set a performance objective of reducing the number of the most serious air traffic control OEs by 15%, to no more than 563, by FY2008. However, the OE rate has increased in recent years (DOT OIG, 2000, 2002, 2003b). For example, the number of OEs increased from 754 in FY1997 to 1,194 in FY2001. Errors declined in FY2002 to 1,061 with the downturn in air traffic following the events of 9-11-2001, but recovered in FY2003. The DOT Inspector General reported that there were 1,186 OEs in FY2003, as shown in Figure 1.

Previous research on OEs investigated factors such as controller workload, situation awareness, shiftwork, fatigue, aircraft flight characteristics, and sector complexity (Della Rocco, Cruz, & Clemens, 1999; Endsley & Rodgers, 1997; Rodgers & Nye, 1993; Rodgers, Mogford, & Mogford, 1998; Schroeder & Nye, 1993). Personnel and organizational factors such as staffing, experience, training, and work attitudes have also been investigated (Broach & Dollar, 2002; Center for Naval Analyses Corporation, CNAC, 1995; Schneider, 2001; Schroeder & Nye, 1993).

The relationship of age to OEs has been considered explicitly in two studies. In 1976, the FAA Air Traffic Service requested that the MITRE Corporation conduct a "study of the performance of the human element in air traffic control … to support identification of system error causes and recommend corrective actions" (Kinney, 1977, p. iii). As part of that study, Spahn (1977) drew on data from the System Effectiveness Information System (SEIS) to investigate the relationship of age to System Errors (SEs; now called Operational Errors[1]). Spahn analyzed data for 630 center and 564 terminal errors that occurred in the years 1974 through 1976. First, Spahn plotted the

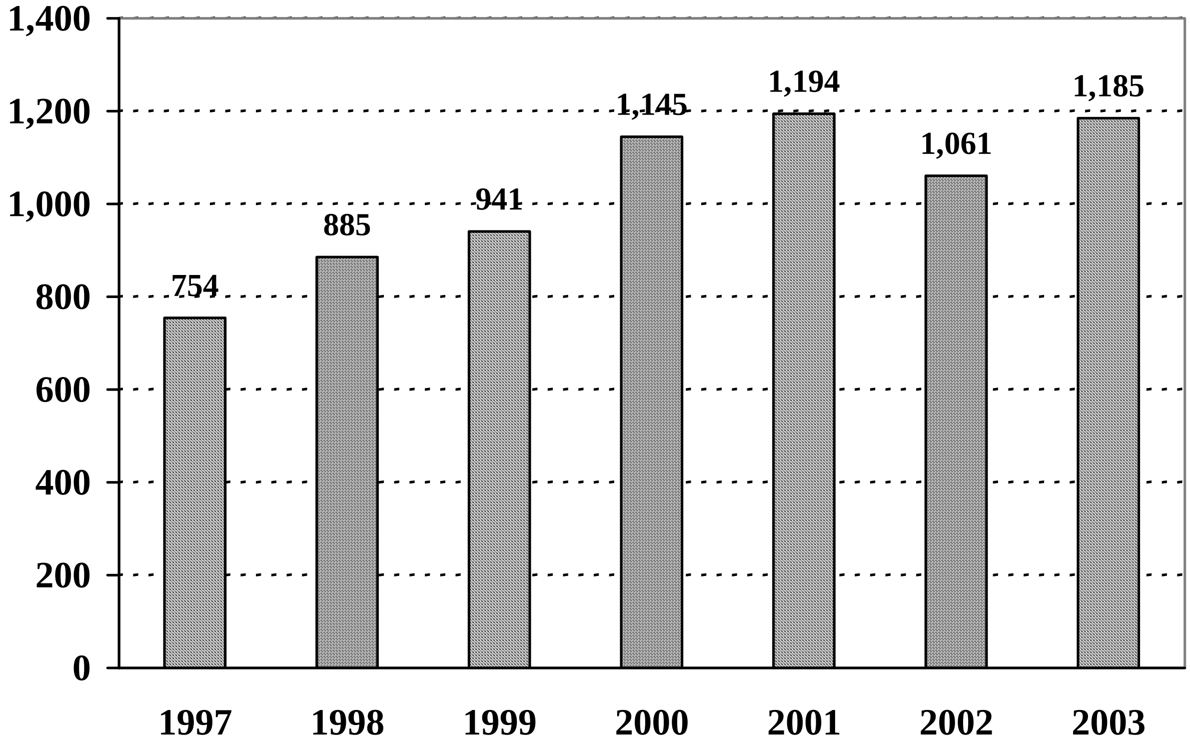

Figure 1: Number of Operational (OEs) by Fiscal Year (FY)

frequency distributions of the age of involved controllers and of the entire controller population by option and year. The frequency distributions, as shown in Figure 2 for center controllers and SEs, were very similar. Based on this inspection and without formal statistical tests, Spahn observed that the similarity showed that "no age group has had neither more nor less than its proportional share of system errors" (pp. 3-35). He concluded that SEs behaved like random events and were not predictable on the basis of controller age (pp. 3-35).

The Center for Naval Analyses Corporation (CNAC) was tasked by the FAA to conduct an analysis of operational errors in the early 1990s. CNAC extracted en route operational error data for the period January 1991 to July 1995 from the FAA Operational Error/Deviation System (OEDS). These data were then matched with agency personnel records and controller experience at the time of the error was estimated. The controllers (N = 3,724) were then grouped by experience, and the total number of controllers with errors was divided by the total number with the same experience to derive an estimate of the "likelihood" of an OE for each experience group. CNAC found that experience and the likelihood of an OE were significantly related, with a quadratic equation fitting the data ($R^2 = .72$). CNAC reported that the likelihood of an OE declined dramatically in the first few years of experience at an air route traffic control center (ARTCC) and then appeared to approach a constant value. Experience was significantly correlated with age ($r = .48$, $p < .001$), but CNAC did not examine controller age or control for age effects.

Broach (1999) re-analyzed the CNAC data from the perspective of controller age. The CNAC data set included the number of OEs (none, one, two, or more) committed between January 1991 and July 1995. OE dates were not available, so age at the time of the error could not be calculated. Therefore, the analysis by Broach were based on age and experience at the beginning of the 5-year observation period.[2] Following the CNAC methodology, the controllers were grouped by age in 1-year increments from 18 to 48. The average age at the beginning of the observation period was calculated (AGE). The total number of controllers with errors was divided by the total number of controllers in that age group to estimate the likelihood of an OE for each group (p(OE)). The average experience (EXP), defined as years of experience at the facility, was also computed for each age group. Two analyses were performed. First, OE likelihood was regressed on AGE, using the SPSS® CURVEFIT procedure. This provided an estimate of age effects. However, as age and experience were confounded in the CNAC data, a second analysis was conducted in

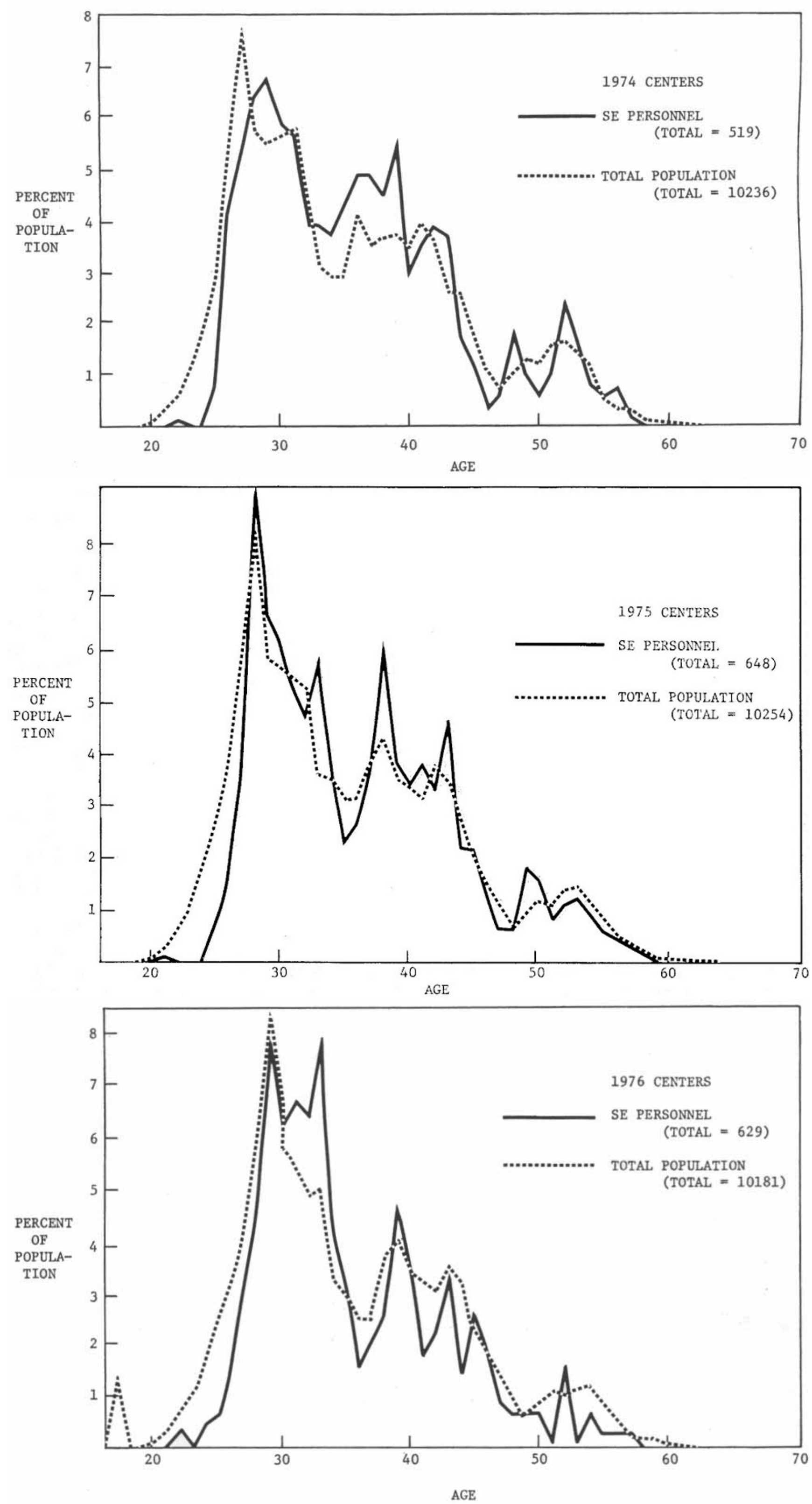

Figure 2: Distribution of System Errors relative to the age distribution of en route controllers, 1974, 1975, and 1976 (Spahn, 1977)

which OE likelihood was regressed on both age and experience to provide an initial estimate of the relative contributions of both. Age and experience accounted for about 45.0% of the variance in OE likelihood across age groups (R = .671, $F(2,27)$ = 11.03, p < .001). The standardized regression coefficient (β) for experience was negative (β = -.452), compared with a positive coefficient for age (β = 1.06). The results of that regression analysis indicated that the likelihood of an en route OE might increase with controller age. This suggested that, as the post-strike controller population ages (Schroeder, Broach, & Farmer, 1998), the likelihood of OEs may increase. However, the regression analysis also found that experience might mitigate the risk of an OE with increasing age. Additional research on the relationship between chronological age, experience, and the incidence of operational errors was recommended in view of the aging of the controller workforce. The present study builds on that recommendation.

Methodological Considerations

As noted by Li (1994) and Broach (2004), analysis of adverse, rare outcomes such as OEs and aircraft accidents poses analytic and methodological challenges. Common approaches include (a) analysis of the characteristics of the adverse outcome of interest and (b) analysis of the rates at which an adverse outcomes occur. The description of the characteristics of "severe" en route OEs by Rodgers and Nye (1993) is an example of the first descriptive approach. The analysis of OE rates by CNAC (1995), Broach (1999), and Broach and Dollar (2003) are examples of the second approach. Both CNAC and Broach calculated the dependent variable of interest as the ratio of controllers with errors in an experience or age range to the total number of controllers in that experience or age range. CNAC labeled this ratio as the "likelihood" of involvement in an error. In fact, both CNAC and Broach calculated the proportion of controllers in a given category that were involved in an error during some observation period. The result is a *person*-based estimate of risk. However, a person-based estimate of risk does not take into account factors such as aptitude, experience, age, and exposure. Exposure is a critical variable in assessing the risk for the occurrence of an adverse event. For example, a controller working a busy, low-altitude transitional sector with multiple merging airways that feed a major hub during an afternoon rush will have a greater opportunity to commit an OE than another controller working a high-altitude sector with sparse cross-continental traffic in steady, predictable east/west flows. Time on position may vary as well. A controller working longer on a given position will have greater opportunity to commit an OE than another controller working less time on a position. As noted by Della Rocco, Cruz, and Clemens (1999), a measure of exposure is required to appropriately analyze the risk of being involved in an OE. However, detailed measures of controller exposure were not available for this study.

Without measures of exposure, the analytic focus shifts from rates to the occurrences themselves. OEs are rare events, relative to the number of controllers working and operations conducted in any given day or year. On one hand, an event such as an OE may occur in any of a large number of operations. On the other hand, the probability of occurrence in any given trial is small. Events with these characteristics often follow the Poisson distribution rather than the more familiar bell-shaped normal distribution (Cameron & Trivedi, 1998).

A Poisson distribution has a single parameter, λ, unlike the more familiar normal distribution that is characterized by two parameters, the mean and standard deviation. The normal distribution is typically portrayed as a symmetrical bell curve (Figure 3). In contrast, the Poisson distribution may be asymmetrical and skewed, depending on the value of λ. For example, for small values of λ, the resulting distribution is peaked nearer to 0 and has a long "tail" to the right (Figure 4). Larger values of λ result in a distribution that looks more like a normal distribution.

Examples of events that follow a Poisson distribution are doctor visits, absenteeism in the workplace, mortgage pre-payments and loan defaults, bank failures, insurance claims, and airplane accidents (Cameron & Trivedi, p. 11). This statistical "law of rare events" might apply to air traffic control operations as well: There are a large number of aircraft under the control of a relatively large number of controllers at any given moment, but the likelihood of an OE for any given aircraft by any single controller is very small.

Familiar statistical techniques based on the normal distribution such as correlation, analysis of variance, and multiple linear regression are not appropriate for modeling rare events characterized by a Poisson distribution. Rather, techniques based on the Generalized Linear Model (GzLM) are more appropriate for modeling dependent variables following a Poisson, Binomial or other exponential distribution (Myers, Montgomery, & Vining, 2002). In the GzLM, a discrete variable such as the count of errors during some observation period is modeled as a function of explanatory variables (which may also follow an exponential distribution). An important assumption in the GzLM is that the events are independently and identically distributed (*iid*).[3] In other words, the occurrence of the event does not depend on other occurrences, but rather depends on the influence of the explanatory variables. For example, the *iid* assumption stipulates that

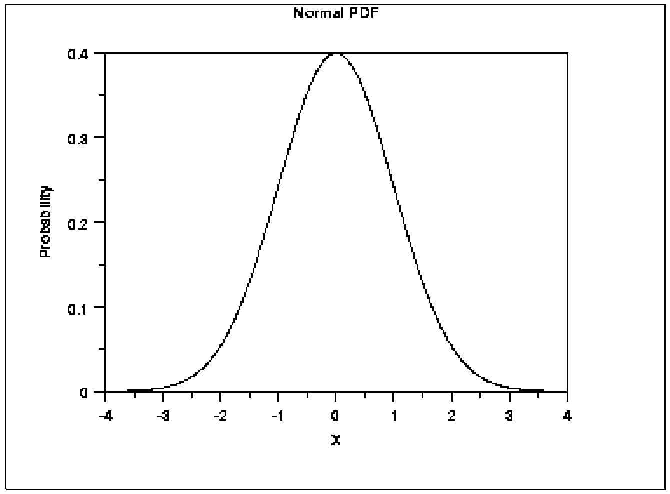

Figure 3: Example of the normal distribution
(From www.itl.nist.gov/div898/handbook/eda/section3/
eda3661.htm, January 6, 2004)

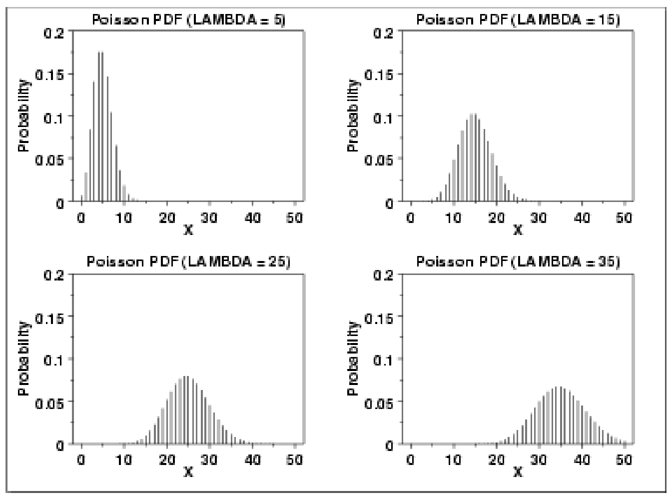

Figure 4: Examples of Poisson distribution for 4 different values of λ (From www.itl.nist.gov/div898/handbook/eda/section3/eda366j.htm, January 6, 2004)

involvement of a controller in an OE in sector X in the afternoon does not depend on the occurrence of an OE in sector Y in the morning, but rather depends on the characteristics of the involved controller, the traffic, or other explanatory variables. Given this assumption, each unit of observation (a fiscal year) is treated as an independent observation for each controller and the number of errors incurred each year modeled as a function of controller characteristics (e.g., age and experience).

Poisson regression is a specific technique from the broad class of GzLM approaches often used to model counts of an event as a function of explanatory or predictor variables in field such as economics and epidemiology. Given that OEs are rare events and their distribution approximates the Poisson distribution, Poisson regression was selected as the appropriate analytic methodology. The goal of the analysis was to model the number of en route OEs incurred by a controller as a function of age and experience (e.g., tenure in the FAA) over a specific period of observation.

METHOD

Source Data

Operational error data. The FAA Operational Error/Deviation System (OEDS) is the official source for operational error data. For this analysis, the Field Support Division (ATX-200) extracted records for en route errors occurring between October 1, 1993, and September 30, 2003. An Excel® data file was received from ATX-200, with 6,337 error records for the period October 1, 1993, through September 30, 2003. The data elements from the FAA Form 7210-3 (08/02) included in the raw data file are listed in Table 1. Due to database changes, only records from October 1, 1996 through September 30, 2003, were usable for the analysis. The following criteria were used to select error records for analysis:

- Event Date >= 10/01/1996
- Primary ATCS only (P)
- Valid ATCS (partial) ID (Last 4 or 6 digits of SSN)
- Valid ATCS Date-of-Birth (DOB)
- Valid ARTCC 3-letter facility ID

Review of resulting 3,524 records indicated that most records used the last 4 rather than the last 6 digits of the ATCS SSN as the record identifier. To standardize the identifier, all records were reviewed, and only the last 4 digits of any ID string were used (e.g., last 4 digits of the SSN). Approximately 100 records were corrected.

Actual On-Board (AOB) data. The official system of records for personnel data is the FAA Consolidated Personnel Management Information System (CPMIS). Since 1996, the Civil Aerospace Medical Institute has received an extract of CPMIS data at the end of each fiscal year for research purposes. Each extract was appended to create a cumulative AOB file which was then reduced by selecting records for en route controllers using these criteria: (a) job series = 2152, (b) organization type = ARTCC, and (c) supervisory status = Non-supervisor.

The data file was aggregated by SSN, retaining date of birth (DOB) for matching with the OE data. A new variable was created with the last 4 digits of each controller's SSN. These CPMIS records were then matched with the OE records using the SPSS table lookup procedure (see Figure 5). Two OE records with the same last 4 digits of the SSN and dates-of-birth were dropped. Overall, 3,368 OE records were matched with CPMIS data. Selecting on supervisory status for non-supervisors only resulted in a total 3,054 OE records.

Table 1: OEDS data elements included in OE data extract

Form Block	Description
Report Number	
Block 1	Date and time (local) of incident
Block 9	Number of aircraft controller had responsibility for at the time of the error
Block 10	Was training in progress?
Block 11	Primary (P) or Contributory (C)
Block 13	Employee's 3-letter facility identification
Block 15	Employee's date of birth
Block 16	Last (4 or 6) digits of employee's social security number
Block 17	Indicate the performance level of the employee
Block 20	Is a medical certification issue related to the incident?
Block 25	Time on position
Block 28	Position function

CPMIS			OEDS			
DOB	LAST4SSN	YEAR	YEAR	LAST4SSN	DOB	N_OE
01/01/53	1234	1997	1997	1234	01/01/53	1
02/02/54	2345	1997	1997	2345	02/02/54	1
…	…	…	…	…	…	…
01/01/53	1234	2003	2003	1234	01/01/53	1
…						

```
(SPSS Syntax)

MATCH FILES
        /FILE=[CPMIS]
        /FILE=[OEDS]
        /BY=YEAR SSN DOB
```

Figure 5: Logic for matching CPMIS and OEDS records by controller and year

Table 2: Number of non-supervisory ATCS on-board with 0, 1, 2, or 3 operational errors by fiscal year

	Number of ATCS with Operational Errors (OEs)				
Fiscal Year	0	1	2	3	AOB Total
1997	6,864	303	11	0	7,178
1998	6,932	389	16	0	7,337
1999	6,869	422	21	0	7,312
2000	6,833	487	31	0	7,351
2001	6,827	549	45	1	7,422
2002	7,110	416	32	0	7,558
2003	7,410	313	17	1	7,741

The 3,054 OE records were then matched with CPMIS records for non-supervisory controllers without errors in any given year to create an overall database comprised of controllers with and without errors for each fiscal year. The number of error and non-error records is presented by fiscal year in Table 2. For example, of the 7,178 non-supervisory ATCS on-board at ARTCCs in FY1997, 6,864 (95.6%) had no operational errors, while 303 controllers (4.2%) had one OE, 11 had 2 errors (0.2%), and none had 3 errors in that fiscal year. However, as shown in Table 2, there was one ATCS in FY2001 and another in FY2003 with three OEs for the year.

Data Transformations

Both age and tenure were continuous ratio variables. To simplify the analysis, they were recoded into specific ranges. The first category for tenure was based on the average of about three years required to complete on-the-job training for center controllers (Manning,1998). The next interval was 6-years wide (4 through 9), followed by 5-year increments. Age was recoded into 2 groups: age 55 and younger; and age 56 and older. This split was used to specifically assess the risk that might be associated with controllers older than the mandatory separation age.

Table 3: Tenure by age cross-classification table for Poisson regression analysis

Tenure Group	Number of OEs (n_{ij})		ATCS Population (N_{ij})	
	LE Age 55	GE Age 56	LE Age 55	GE Age 56
LE 3 Years	44	4	3,587	110
4 – 9 Years	488	10	7,574	191
10 – 14 Years	1,112	20	15,758	280
15 – 19 Years	1,007	2	14,816	128
20 – 24 Years	343	2	5,615	67
GE 25 Years	142	57	2,587	1,186

Analysis

The data were aggregated by fiscal year, age group, and tenure group to create a cross-classification table suitable for Poisson regression, as shown in Table 3. The columns labeled "Number of OEs (n_{ij})" contain the counts of OEs reported for each age and tenure group combination. For example, there were 44 OEs in the period FY1997 to FY2003 for controllers age 55 or less and with 3 years or less tenure, and 4 OEs for controllers age 56 or older and with 3 years or less tenure. The column labeled "ATCS Population (N_{ij})" contain data representing the number of controllers "exposed" to the risk of incurring an OE during the observation period for each age-tenure combination. For example, there were 3,587 en route controllers age 55 or less with 3 years or less tenure who were "at risk" of incurring an OE during the observation period. The goal of the Poisson regression analysis was to assess the relative effects of age and tenure on the ratios of errors to "at risk" population. The SPSS® version 11.5 General Loglinear (GENLOG) method was used to conduct the Poisson regression analysis.

RESULTS

Overall, the Poisson regression model fit the data poorly (Likelihood Ratio $\chi 2$ = 283.81, $p < .001$; see Appendix A for statistical details). The parameter estimate for the main effect of age (3.50) was significantly different from 0 (95% confidence interval = 3.29 to 3.70), as were the parameter estimates for tenure. To consider the effect of age across tenure, the two age groups were contrasted. The Generalized Log Odds Ratio was used to estimate the odds ratio for age, that is, the odds of OE invovlement for older (GE age 56) controllers (see SPSS, 1999, p. 202 - 203). The odds of OE involvement for older controllers (GE age 56) were 1.02 times greater than the odds for younger (LE age 55) controllers, with a 95% confidence interval of 0.42 to 1.64. A confidence interval for the odds ratio that included 1.0 indicated that the odds of involvement for the two groups were equal: neither age group was less or more likely to be involved in an OE.

DISCUSSION

The Poisson regression analysis of the number of OEs as a function of ATCS age and experience (years of employment) did not support the hypothesis that the likelihood of involvement in an en route OE increased with age. This finding casts doubt on the explicit characterization of the mandatory early retirement of controllers as "primarily a safety measure" (Testimony of Donald Francke, U.S. House of Representatives, 1971).

As noted by Li et al. (2003), age in and of itself may have little bearing on safety-related outcomes if factors such as individual job experience, workload, traffic complexity, and time-on-position are taken into consideration (p. 878). Moreover, all other things being equal, age may influence performance through two conflicting pathways. On the one hand, the inevitable changes in cognitive function, particularly speed of processing, may result in slower and less efficient performance. On the other hand, experience is gained with age, and compensatory strategies and meta-strategies may result in safer and more efficient performance by controllers. Additional research is recommended to extend and confirm the initial analyses reported above and to examine the contribution of cognitive and other variables. For example, the en route OE data analyzed in this study might be linked to medical data for each of the controllers such that error involvement as a function of medical status might be investigated. Error data collected using the JANUS approach (Pounds & Isaac, 2002) might be analyzed to determine if certain types of errors, for example, in the cognitive domain, are more or less common for older and younger controllers involved in OEs.

Work on control strategies (D'Arcy & Della Rocco, 2001) might be extended to examine differences in strategies by age and experience groups. In addition, a longitudinal study of a sample of incumbent controllers might be initiated in which, as part of the annual medical examination, additional measures of cognitive function are taken and any changes over time monitored. The sample of controllers might also undergo periodic simulator-based assessments of core technical performance for research purposes only. Other work might focus on investigations of the impact of shift work and fatigue on performance for older controllers and assessment of the efficacy of fatigue counter-measures by age. Annual medical examination data might be used to conduct large-scale epidemiologic studies to track factors such as blood pressure, gastro-intestinal complaints, and other medical outcomes commonly thought to reflect job-related stress.

Finally, in addition to these "controller factors," future research on OEs needs to consider other potential explanatory variables such as traffic and sector architecture. Recent work in the United States (Pfleiderfer, 2003; Mills, Pfleiderfer & Manning, 2002) and Europe (Delahaye & Puechmorel, 2000) has focused on developing metrics for the representation of traffic complexity. While showing promise, there is no scientific agreement as yet on how to measure traffic complexity, much less its interaction in real-time with the controller. However, with continued research on both controller and traffic characteristics, and their interaction, it might be possible to reach a more definitive answer about the relationship of controller age and operational errors.

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END NOTES

[1]The original terminology of System Error is used in describing the MITRE studies to be consistent with the reproduced figures. The more recent terminology of Operational Error (OE) is used in describing contemporary studies. Both terms refer to an event with less than standard separation between aircraft or aircraft and an obstacle as the result of controller action (or inaction).

[2]As is commonly done in survival analyses, age at the beginning of the observation period was used as a predictor of subsequent outcomes (see Li et al., 2003 for an example).

[3]It must be noted that traditional multiple linear regression makes the same assumption that the dependent variable is independently and identically distributed.

[4]This publication and all Office of Aerospace Medicine technical reports are available in full-text from the Civil Aerospace Medical Institute's publications Web site: www.faa.gov/library/reports/medical/oamtechreports/index.cfm

APPENDIX A:
Poisson Regression (GENLOG) SPSS Output

General Loglinear: Without contrasts

```
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                         GENERAL LOGLINEAR ANALYSIS
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Data Information

        12 cases are accepted.
         0 cases are rejected because of missing data.
      3231 weighted cases will be used in the analysis.
        12 cells are defined.
         0 structural zeros are imposed by design.
         0 sampling zeros are encountered.

 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -

Variable Information

Factor     Levels Value

TEN_GRP        6        Service from FAA EOD group
                      1 LE 3 years
                      2 4-9 years
                      3 10-14 years
                      4 15-19 years
                      5 20-24 years
                      6 GE 25 years

AGE_56         2        Under or Over age 56
                      1 LE Age 55
                      2 GE Age 56

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Model and Design Information

 Model: Poisson
Design: Constant + AGE_56 + TEN_GRP

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Correspondence Between Parameters and Terms of the Design

Parameter   Aliased  Term

        1            Constant
        2            [AGE_56 = 1]
        3       x    [AGE_56 = 2]
        4            [TEN_GRP = 1]
        5            [TEN_GRP = 2]
        6            [TEN_GRP = 3]
        7            [TEN_GRP = 4]
        8            [TEN_GRP = 5]
        9       x    [TEN_GRP = 6]

Note: 'x' indicates an aliased (or a redundant) parameter.
```

These parameters are set to zero.

- -

GENERAL LOGLINEAR ANALYSIS

- -

Convergence Information

```
Maximum number of iterations:            20
Relative difference tolerance:         .001
Final relative difference:      3.45689E-06
```

Maximum likelihood estimation converged at iteration 6.

- -

Table Information

Factor	Value	Observed Count	%	Expected Count	%
TEN_GRP	LE 3 years				
AGE_56	LE Age 55	44.00	(1.36)	46.59	(1.44)
AGE_56	GE Age 56	4.00	(.12)	1.41	(.04)
TEN_GRP	4-9 years				
AGE_56	LE Age 55	488.00	(15.10)	483.36	(14.96)
AGE_56	GE Age 56	10.00	(.31)	14.64	(.45)
TEN_GRP	10-14 years				
AGE_56	LE Age 55	1112.00	(34.42)	1098.72	(34.01)
AGE_56	GE Age 56	20.00	(.62)	33.28	(1.03)
TEN_GRP	15-19 years				
AGE_56	LE Age 55	1007.00	(31.17)	979.33	(30.31)
AGE_56	GE Age 56	2.00	(.06)	29.67	(.92)
TEN_GRP	20-24 years				
AGE_56	LE Age 55	343.00	(10.62)	334.86	(10.36)
AGE_56	GE Age 56	2.00	(.06)	10.14	(.31)
TEN_GRP	GE 25 years				
AGE_56	LE Age 55	142.00	(4.39)	193.15	(5.98)
AGE_56	GE Age 56	57.00	(1.76)	5.85	(.18)

- -

Goodness-of-fit Statistics

	Chi-Square	DF	Sig.
Likelihood Ratio	238.8141	5	1.E-49
Pearson	505.8644	5	4.-107

GENERAL LOGLINEAR ANALYSIS

Parameter Estimates

Parameter	Estimate	SE	Z-value	Asymptotic 95% CI Lower	Upper
1	1.7666	.1235	14.31	1.52	2.01
2	3.4968	.1041	33.58	3.29	3.70
3	.0000	.	.	.	.
4	-1.4221	.1608	-8.84	-1.74	-1.11
5	.9173	.0839	10.94	.75	1.08
6	1.7384	.0769	22.62	1.59	1.89
7	1.6234	.0776	20.93	1.47	1.78
8	.5502	.0890	6.18	.38	.72
9	.0000	.	.	.	.

Covariance Matrix of Parameter Estimates

Parameter	1	2	4	5	6	7	8
1	.0152						
2	-.0105	.0108					
4	-.0050	.0000	.0259				
5	-.0050	.0000	.0050	.0070			
6	-.0050	.0000	.0050	.0050	.0059		
7	-.0050	.0000	.0050	.0050	.0050	.0060	
8	-.0050	.0000	.0050	.0050	.0050	.0050	.0079

Aliased parameters are not shown.

Correlation Matrix of Parameter Estimates

Parameter	1	2	4	5	6	7	8
1	1.0000						
2	-.8187	1.0000					
4	-.2531	.0000	1.0000				
5	-.4853	.0000	.3726	1.0000			
6	-.5295	.0000	.4065	.7795	1.0000		
7	-.5248	.0000	.4029	.7725	.8428	1.0000	
8	-.4573	.0000	.3511	.6731	.7344	.7278	1.0000

Aliased parameters are not shown.

```
SAVE OUTFILE='D:\Count-oriented Regression\NonSup Data Agg by FY, Age Group &
Tenure Group.sav'
 /COMPRESSED.

GENLOG
  ten_grp age_56  /GLOR = age_cont
  /MODEL = POISSON
  /PRINT = FREQ ESTIM CORR COV
  /PLOT = NONE
  /CRITERIA = CIN(95) ITERATE(20) CONVERGE(.001) DELTA(.5)
  /DESIGN age_56 ten_grp  .
```

General Loglinear: Age Contrast

```
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                          GENERAL LOGLINEAR ANALYSIS
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Data Information

        12 cases are accepted.
         0 cases are rejected because of missing data.
      3231 weighted cases will be used in the analysis.
        12 cells are defined.
         0 structural zeros are imposed by design.
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Variable Information

Factor     Levels Value

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                      1 LE Age 55
                      2 GE Age 56
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Model and Design Information

 Model: Poisson
Design: Constant + AGE_56 + TEN_GRP

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        7            [TEN_GRP = 4]
        8            [TEN_GRP = 5]
        9       x    [TEN_GRP = 6]

Note: 'x' indicates an aliased (or a redundant) parameter.
      These parameters are set to zero.
```

GENERAL LOGLINEAR ANALYSIS

Convergence Information

```
Maximum number of iterations:            20
Relative difference tolerance:         .001
Final relative difference:      3.45689E-06

Maximum likelihood estimation converged at iteration 6.
```

Table Information

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AGE_56	GE Age 56	4.00	(.12)	1.41	(.04)
TEN_GRP	4-9 years				
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AGE_56	GE Age 56	10.00	(.31)	14.64	(.45)
TEN_GRP	10-14 years				
AGE_56	LE Age 55	1112.00	(34.42)	1098.72	(34.01)
AGE_56	GE Age 56	20.00	(.62)	33.28	(1.03)
TEN_GRP	15-19 years				
AGE_56	LE Age 55	1007.00	(31.17)	979.33	(30.31)
AGE_56	GE Age 56	2.00	(.06)	29.67	(.92)
TEN_GRP	20-24 years				
AGE_56	LE Age 55	343.00	(10.62)	334.86	(10.36)
AGE_56	GE Age 56	2.00	(.06)	10.14	(.31)
TEN_GRP	GE 25 years				
AGE_56	LE Age 55	142.00	(4.39)	193.15	(5.98)
AGE_56	GE Age 56	57.00	(1.76)	5.85	(.18)

Goodness-of-fit Statistics

	Chi-Square	DF	Sig.
Likelihood Ratio	238.8141	5	1.E-49
Pearson	505.8644	5	4.-107

- -

GENERAL LOGLINEAR ANALYSIS

- -

Parameter Estimates

Parameter	Estimate	SE	Z-value	Asymptotic 95% CI Lower	Asymptotic 95% CI Upper
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2	3.4968	.1041	33.58	3.29	3.70
3	.0000	.	.	.	.
4	-1.4221	.1608	-8.84	-1.74	-1.11
5	.9173	.0839	10.94	.75	1.08
6	1.7384	.0769	22.62	1.59	1.89
7	1.6234	.0776	20.93	1.47	1.78
8	.5502	.0890	6.18	.38	.72
9	.0000	.	.	.	.

- -

Covariance Matrix of Parameter Estimates

Parameter	1	2	4	5	6	7	8
1	.0152						
2	-.0105	.0108					
4	-.0050	.0000	.0259				
5	-.0050	.0000	.0050	.0070			
6	-.0050	.0000	.0050	.0050	.0059		
7	-.0050	.0000	.0050	.0050	.0050	.0060	
8	-.0050	.0000	.0050	.0050	.0050	.0050	0079

Aliased parameters are not shown.

- -

Correlation Matrix of Parameter Estimates

Parameter	1	2	4	5	6	7	8
1	1.0000						
2	-.8187	1.0000					
4	-.2531	.0000	1.0000				
5	-.4853	.0000	.3726	1.0000			
6	-.5295	.0000	.4065	.7795	1.0000		
7	-.5248	.0000	.4029	.7725	.8428	1.0000	
8	-.4573	.0000	.3511	.6731	.7344	.7278	.0000

Aliased parameters are not shown.

```
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                          GENERAL LOGLINEAR ANALYSIS
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Generalized Log-odds Ratio Coefficients

Factor          Value            AGE_CONT


TEN_GRP  LE 3 years
 AGE_56    LE Age 55               -1.000
 AGE_56    GE Age 56                1.000

TEN_GRP   4-9 years
 AGE_56    LE Age 55               -1.000
 AGE_56    GE Age 56                1.000

TEN_GRP 10-14 years
 AGE_56    LE Age 55               -1.000
 AGE_56    GE Age 56                1.000

TEN_GRP 15-19 years
 AGE_56    LE Age 55               -1.000
 AGE_56    GE Age 56                1.000

TEN_GRP 20-24 years
 AGE_56    LE Age 55               -1.000
 AGE_56    GE Age 56                1.000

TEN_GRP GE 25 years
 AGE_56    LE Age 55               -1.000
 AGE_56    GE Age 56                1.000

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 Generalized Log-Odds Ratio
                                                          95% Confidence Interval
 Variable      Value         SE         Wald    Sig.         Lower       Upper

 AGE_CONT   -20.9810      .6248   1127.4890 3.5-247     -22.2056    -19.7563

- - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -

 Generalized Odds Ratio
                         95% Confidence Interval
 Variable      Value         Lower       Upper

 AGE_CONT  7.728E-10     2.2710E-10  2.6300E-09
```