Working Paper 8811

FEDERAL GRANT POLICIES AND PUBLIC SECTOR SCRAPPAGE DECISIONS

by Brian A. Cromwell

Brian A. Cromwell is an economist at the Federal Reserve Bank of Cleveland. The author would like to thank Erica Groshen, Paul Bauer, Randall Eberts, William Wheaton, and especially James Poterba for useful suggestions and discussion. William Lyons and Dottie Nicholas of the Transportation System Center provided invaluable assistance with the data. Financial support from the National Graduate Fellowship Program and the M.I.T. Center for Transportation Studies is gratefully acknowledged.

November 1988

Introduction

This paper examines the impact of federal grant policies on capital scrappage decisions by local governments. Large subsidies for new capital potentially shorten equipment life by inducing substitution of new capital for the maintenance of existing capital, leading to shorter equipment life than would occur under cost-minimization. This distortion provides one possible explanation for the "infrastructure crisis" that has drawn recent attention in political and media circles.[1]

In a companion paper, I demonstrate that vehicle maintenance spending is significantly higher among private owners of transit capital than among public owners of similar equipment, suggesting that federal subsidies distort local public capital decisions.[2]

The present paper uses newly developed hazard model estimators to examine scrappage decisions in the public and private sectors. The results demonstrate that federal policy has important effects on local public scrappage decisions.

The operations research literature includes extensive analysis of scrappage and maintenance decisions and of the implied conditions for optimal equipment life and maintenance policies.[3] A model from this tradition is used to examine the impact of federal capital subsidies on local decisions and to show that a subsidy for new capital purchases (but not for maintenance of existing capital) will induce local governments to scrap equipment before the optimal scrappage point. The bias in federal policy towards subsidizing capital purchases versus operating expenses thus offers a potential explanation for the perceived excessive deterioration in the local public capital stock.

To examine the importance of federal grant policies for local scrappage decisions, I use hazard modeling techniques with a new data set on operations and vehicle fleets of local mass-transit providers. The data, collected by the Urban Mass Transportation Administration (UMTA), provide an unusually precise measure of the physical capital stock of 436 public and private transit properties nationwide. The empirical analysis uses estimators common to studies of unemployment duration, including the Kaplan-Meier empirical hazard estimator, a fully-parametric proportional hazard estimator, and Meyer's (1988) semiparametric hazard estimator (SPHE). The results demonstrate the advantages of SPHE and provide strong evidence that federal grant policies have a direct impact on local scrappage decisions.

The paper is organized as follows. Section 1 uses a model of optimal equipment life to predict the impact of federal grants on scrappage decisions. Section 2 discusses the data set and federal grant policies for mass-transit capital. Sections 3 and 4 present the Kaplan-Meier and the fully-parametric proportional hazard model estimates, respectively. Section 5 presents results using SPHE and discusses the differences between

SPHE and the previous estimators. Finally, section 6 presents conclusions and discusses the implications of the results for federal grant policies.

I. A Model of Optimal Equipment Life

This section models scrappage to demonstrate the impact of federal subsidies on optimal equipment life.[4] Consider a cost-minimizing firm or local government that decides when to scrap a machine it already owns. We assume that the machine is not replaced when scrapped and that maintenance $M(t)$ increases while operating receipts $Q(t)$ decrease over time. The firm chooses the scrappage time T that maximizes the present value of net receipts, $A(T)$, flowing from the machine

$$(1) \qquad A(T) = \int_0^T e^{-rt} \left[Q(t) - W^m M(t)\right] d_t - q,$$

where W^m is the price of maintenance and q is the purchase price of the machine. Setting $A'(T) = 0$ yields first-order condition

$$(2) \qquad \left[\ Q(T) - W^m M(T)\ \right] e^{-rT} = 0,$$

which holds that equipment is scrapped when the return on it is offset by necessary maintenance expenditures. Notice that in this simple problem, with no replacement, the price of new capital does not affect scrappage decisions.

If a machine is replaced by an identical machine when scrapped, and if this process continues indefinitely, the firm's problem then is to choose T to maximize $B(T)$, the discounted value of net receipts from this sequence.

$$(3) \qquad B(T) = \sum_{k=0}^{\infty} e^{-rTk} \, [\; A(T) \;]$$

Setting $B'(T) = 0$ yields first-order condition (4) that

$$(4) \qquad \left[\; Q(T) - W^m M(T) - rB(T) \right] \frac{e^{-rT}}{(1-e^{-rT})} = 0$$

shows that scrappage occurs when the current accrual of costs $Q(T) \cdot W^m M(T)$, equals the long-run average costs of the infinite sequence, $rB(T)$.

Noting that the purchase price enters this condition through the definitions of $B(T)$ and $A(T)$, we can use standard comparative statics to show the effects of subsidies on scrappage decisions. Substituting these definitions into (4) and noting that $B(T) = A(T)/(1 - e^{-rT})$ yields

$$(5) \qquad (Q(T) - W^m M(T))(1 - e^{-rT}) - r\left[\int_0^T e^{-rt}(Q(t) - W^m M(t))dt - q\right] = 0,$$

which forms an implicit function $\Psi(T, q, W^m) = 0$. We then have

$$\Psi_T = (Q' - W^m M')(1 - e^{-rT}) < 0$$

$$\Psi_q = r > 0, \text{ and}$$

$$\Psi_W = - \left[M(T)(1 - e^{-rT}) - r\int_0^T e^{-rt} M(t)\,dt \right]$$

$$= - M(T) \left[1 - e^{-rT} - r\int_0^T e^{-rt} \frac{M(t)}{M(T)}\,dt \right]$$

$$< - M(T) \left[1 - e^{-rT} - r\int_0^T e^{-rt}\,dt \right] = 0$$

yielding $\frac{dT}{dq} = \frac{-\Psi_q}{\Psi_T} > 0$ and $\frac{dT}{dW^m} = \frac{-\Psi_W}{\Psi_T} < 0$.

It follows that a federal subsidy for new capital purchases at a matching rate $G^c{}_f$ lowers the effective equipment price to $(1 - G^c{}_f)q$ and reduces the optimal equipment life T* chosen by a local government. A federal subsidy for operating expenses at matching rate $G^o{}_f$, however, reduces the effective maintenance price to $(1-G^0{}_f)W^m$ and would raise T*. If both subsidies are in place, the net effect on T* is ambiguous.

Similar arguments hold for a private firm that receives tax benefits from new investment through investment tax credits c and the present value of depreciation deductions τz, yielding an effective equipment price of $(1 - c - \tau z)q$, but deducts maintenance expenses from profits, yielding an effective maintenance price of $(1 - \tau)W^m$.

Consider a federal subsidy that can only be used to replace equipment that is as least as old as some $\bar{T}$, so that $q = q_1$ for $T < \bar{T}$ and that $q = q_2 = (1 - G^c{}_f)q_1$ for $T \geq \bar{T}$. From the comparative statics results we have that $T^*{}_1(q_1) > T^*{}_2(q_2)$ and will observe the following pattern of scrappage:

if $T^*{}_1 < \bar{T}$, then scrappage occurs at $T = T^*{}_1$ and no capital grant is received;

if $T^*{}_2 > \bar{T}$, then scrappage occurs at $T = T^*$, and a capital grant is received; 'finally,

if $T^*{}_2 \leq \bar{T} < T^*{}_1$, then scrappage occurs at $T = \bar{T}$ with a capital grant received.

Because of variations in operating conditions and wage rates across firms we can expect that T* would be distributed across a sample of properties. Given a grant structure of this type, we would then expect to see a marked shift in the overall scrappage rate at $T = \bar{T}$. This paper will examine a subsidy program with a structure similar to that above and test if the observed scrappage follows the predicted pattern.

II. Data on Local Mass-Transit Providers

The local mass-transit industry is the focus of the empirical analysis for several reasons. First, the production processes of transit providers are relatively homogeneous and their inputs (labor hours and vehicle miles) are measurable. This facilitates comparisons of cost-efficiency across transit providers. Second, the stock of transit capita is also relatively homogenous and can be measured from fleet and mileage data. Finally, transit service is provided by a heterogeneous set of institutions -- including city governments, regional authorities, public agencies managed by private concerns, and wholly private operators. Thes providers receive revenues from a wide variety of sources -- including fares, federal operating assistance, state and federal capital grants, local general revenues, and local dedicated taxes. By controlling for operating conditions and wage rates, I use this heterogeneity to examine the impact of subsidies on scrappage.

Data

The data used here are collected under the Section 15 Reporting System administered by the Urban Mass Transportation Administration (UMTA Section 15 of the Urban Mass Transportation Act (UMT Act), establishes a uniform accounting system for public mass transportation finances and operations. All applicants and beneficiaries of Federal assistance under Section 9 of the UMT Act are subject to this system and are required to file annual reports with UMTA.[5]

Section 15 data for fiscal year (FY) 1979 through FY 1985 are available for 435 transit systems and include detailed information on revenue sources, expenses, employees, and hours and miles of service provided.[6] These data provide an unusually detailed panel of local governments' physical assets. In particular, vehicle inventories for each system are broken down by model, year of manufacture, and mileage.

The sample was limited to 112 properties that only ran bus service -- as opposed to rail, ferry, etc. -- and that had more than five vehicles. By tracking vehicles across the 1982 through 1985 reporting years, scrappage decisions were observed for 15,829 vehicles, including 1,005 privately owned vehicles from 11 privately owned companies. Vehicles that changed from active to inactive status or that were dropped from the fleets between report years were counted as scrapped.

Federal Transit Policies

The federal government finances a major part of local public mass transportation. The largest component of federal transit aid is the Section 3 discretionary grant program that funds up to 75 percent of approved capital expenditures by local transit authorities. A majority of these grants pay for major construction projects and expansions of large transit properties with rail systems. The principal federal grant program for properties that only operate bus lines is the Section 9 formula grant program that distributes funds to urbanized areas for use in transit operating and capital expenditures. Due to a desire by UMTA to wean local properties away from operating assistance, the Surface Transportation Act of 1982 capped the level of funds available for operating assistance for FY 1983 and beyond to some 90 percent of the FY 1982 level, or to 50 percent of a property's operating deficit, whichever was lower. The overwhelming majority of public-transit properties are constrained by the cap and receive no operating assistance on the margin. The Section 9 capital funds are principally used for vehicle replacement and pay up to 80 percent of the cost of a new vehicle.

Federal control over maintenance principally consists of setting an upper limit for deterioration of federally purchased equipment. UMTA requires local transit properties to operate buses purchased with federal funds for at least 12 years or 500,000 miles.[7] Failure to do so results in a penalty in federal assistance for new capital purchases. This 12-year limit, however, is below the potential operating life of 15 to 20 years for standard bus models. UMTA also requires that the number of spare vehicles available at periods of maximum service be no higher than 20 percent, thus putting an upper limit on fleet size. This guideline, however, is not as rigorously enforced as the 12-year vehicle life guideline.[8]

As shown in section 1, the structure of the UMTA grants leads to the prediction that in the public sector we will observe low levels of scrappage before the 13-year point, a marked shift in the scrappage at 13 years, then high levels of scrappage thereafter. A similar pattern for privately-owned vehicles is unlikely as they are not subject to such a discontinuity in the price of new equipment.

Used-Bus Market

The definition of scrappage used here has drawbacks since the disposition of equipment is not reported in the Section 15 data. The used-bus market is highly fragmented and is ad hoc in nature. No central data source of used-bus prices or sales exists. UMTA officials report, however, that the used transit bus market is depressed. The supply of public vehicles over 12 years old far exceeds demand and vehicles are most commonly sold for scrap. To confirm this, I collected transaction prices for some 645 transit vehicles sold in 1987 and 1988 by contacting all properties that solicited bids for used vehicles during this period.[9]

The results of this survey are shown in table 1. Prices for publicly owned vehicles manufactured before 1971 ranged from $100 to $3500 with an average price of $511. Even vehicles reported to be well-maintained typically did not sell for over $3,000. Prices for vehicles manufactured between 1971 and 1975 ranged from $250 for scrapped vehicles to $6,000 for well-maintained vehicles. Prices for newer vehicles manufactured between 1976 and 1980 averaged $8,863.

Typically, less than 10 bids were received per auction with a mean of five bids reported by properties that would provide this information. Those bidding included Caribbean nations, church groups,

Table 1
Used Transit Vehicle Prices
in 1987 and 1988

Year of Manufacture	Average Price($)	Max.	Min.	Number of Observations
Public				
1961-65	$ 301	$ 1000	$ 100	255
1966-70	841	3500	400	163
1971-75	1648	6000	250	239
1976-80	8863	17000	3300	8
Private				
1961-65	$ 3500	---	---	11
1966-70	6590	---	---	11
1971-75	7500	---	---	9
1976-80	18000	---	---	1

Source: Telephone survey by author.

charter-bus operators, people planning to make recreational vehicles, and farmers in need of storage space. If the vehicles were purchased with federal funds, UMTA collected 80 percent of the proceeds with an allowance made for administrative expenses. The costs of soliciting bids or holding an auction, however, often were reported to exceed the remaining local share. Given the low prices received for even well-maintained vehicles, salvage and resale values represent a negligible percentage of the total cost of owning and operating transit equipment and are assumed not to affect maintenance and scrappage decisions.

The private properties consist of seven in the New York metropolitan area with the rest scattered across the country.[10] Their inclusion in the Section 15 data results from contracting with a public recipient of Section 9 funds to provide transit services. As these contracts often provide for the leasing of public vehicles, care was taken to examine scrappage decisions only on vehicles owned outright by private operators. I was able to obtain used-vehicle prices for a much smaller sample of privately owned vehicles. These prices, also shown in table 1, suggest that the private vehicles are in better condition and command a higher price, with prices averaging from $3,500 to $7,500 for vehicles manufactured before 1976. Other private companies, however, reported selling their vehicles for scrap at the depressed prices similar to those received by public agencies. Again, given the depressed nature of the used-bus market, it is assumed that resale and scrap value does not affect scrappage decisions.

III. Empirical Hazard Estimates

This section presents nonparametric Kaplan-Meier estimates of the baseline hazard for public and private vehicles. These estimates are presented in tables 2 and 3, respectively. The hazards are also plotted, with 95 percent confidence intervals, in figures 1 and 2. The Kaplan-Meier estimator directly estimates the hazard function from the sample of vehicles. For each time t, the number of failures $D(t)$ (that is, the number of vehicles scrapped) is divided by the total number of vehicles at risk at the start of time t, $R(t)$.[11] Censored spells (that is, vehicles that are not observed to be scrapped) are included in the risk set previous to their censor time and are dropped thereafter. This treatment of censoring yields a consistent estimate of the true hazard at each time t as long as the censoring mechanism and vehicle age are independent of each other. Since censoring in this sample is due to the lack of data after 1985 for vehicles of all ages, this is a reasonable assumption. A further assumption of this estimator is that the population is homogenous across time, a not unreasonable assumption for the GMC and Flxible New-Look buses manufactured in the pre-1977 period. Observations of vehicles lasting more than 20 years were truncated at 20. Less than 4 percent of observed vehicles were active after this age and strong parametric assumptions would be needed to make inferences about them.

The estimates in general demonstrate the importance of federal grant policies for public-sector scrappage. The hazard for public vehicles

Table 2
Public Vehicles: Failures, Censorings, and the Kaplan-Meier Empirical Hazard

Age t	Risk Set R(t)	Failures D(t)	Censorings C(t)	Hazard H(t)	Standard error
1	2621	84	621	0.0320	0.0034
2	3880	124	1117	0.0320	0.0028
3	3448	103	593	0.0299	0.0029
4	3095	46	1897	0.0149	0.0022
5	2037	33	792	0.0162	0.0028
6	2242	106	327	0.0473	0.0045
7	2381	67	715	0.0281	0.0034
8	3088	95	1020	0.0308	0.0031
9	2738	175	412	0.0639	0.0047
10	2701	83	1368	0.0307	0.0033
11	1471	50	705	0.0340	0.0047
12	1201	20	500	0.0167	0.0037
13	1041	116	202	0.1114	0.0098
14	1103	120	330	0.1088	0.0094
15	1227	255	208	0.2078	0.0116
16	1082	209	157	0.1932	0.0120
17	1129	196	400	0.1736	0.0113
18	997	313	172	0.3139	0.0147
19	712	263	154	0.3694	0.0181
20	676	134	542	0.1982	0.0153

Note: 2592 failures were observed and 12,232 censorings.
Source: Calculated from Section 15 data, 1982 - 1985 report years.

Table 3
Private Vehicles: Failures, Censorings, and the Kaplan-Meier Empirical Hazard

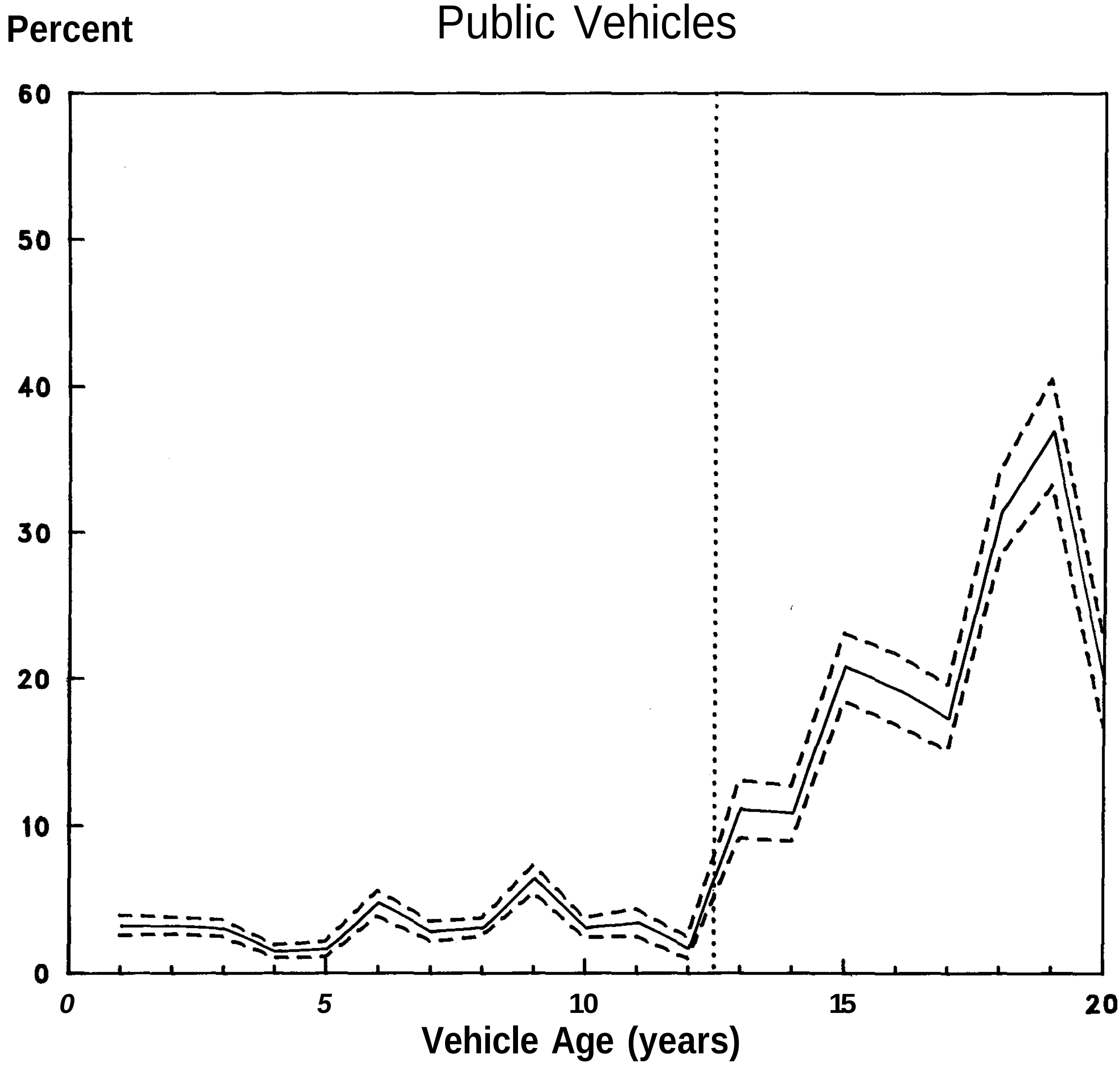
Age t	Risk Set R(t)	Failures D(t)	Censorings C(t)	Hazard H(t)	Standard error
1	28	0	18	0.0000	0.0000
2	42	1	0	0.0238	0.0235
3	47	1	10	0.0213	0.0210
4	129	0	30	0.0000	0.0000
5	111	1	6	0.0090	0.0090
6	121	0	93	0.0000	0.0000
7	114	9	2	0.0789	0.0253
8	133	6	11	0.0451	0.0180
9	192	6	83	0.0313	0.0126
10	105	6	24	0.0571	0.0227
11	133	12	63	0.0902	0.0248
12	143	1	1	0.0070	0.0070
13	213	20	39	0.0939	0.0200
14	203	16	72	0.0788	0.0189
15	209	28	53	0.1340	0.0236
16	215	39	33	0.1814	0.0263
17	167	56	46	0.3353	0.0365
18	88	20	38	0.2273	0.0447
19	140	65	11	0.4643	0.0421
20	85	26	59	0.3059	0.0500

Note: 313 failures were observed and 692 censorings.
Source: Calculated from Section 15 data, 1982 - 1985 report years.

Figure 1

Scrappage Rate

Public Vehicles

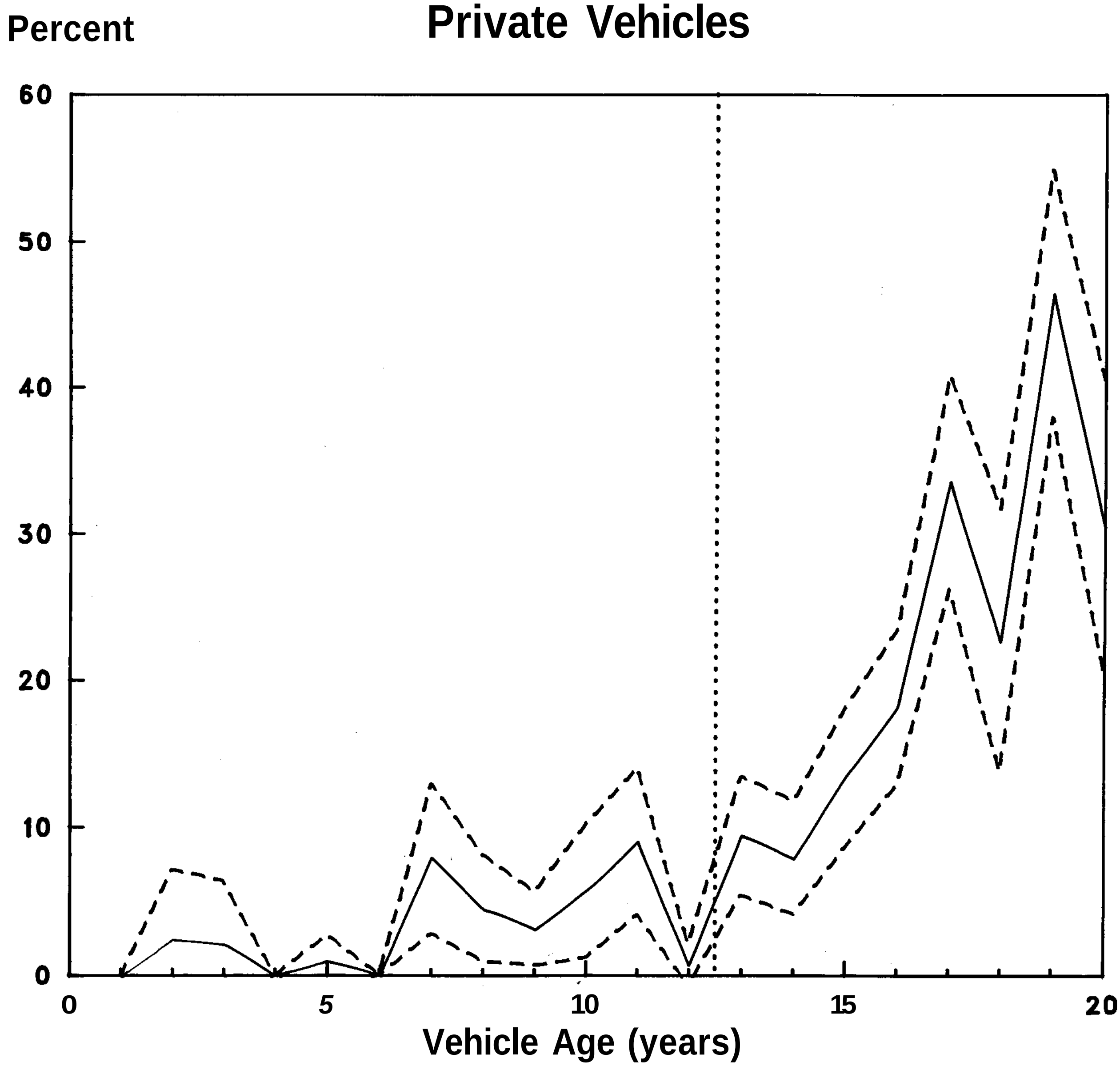


Source: Author's Calculations

Figure 2

Scrappage Rate

Private Vehicles



Source: Author's Calculations

averages under 4 percent for years prior to age 13, then jumps to over 11 percent at age 13, decreases slightly at age 14, then rises steadily to 37 percent by age 19. Standard errors calculated for these estimates suggest that the public hazards are measured with much precision and that the shift at the 13-year point is statistically significant.[12]

The private estimates are estimated with less precision and exhibit more volatility, but in general show a rise in scrappage from near 0 for the 1- to 6-year period to an average 5 percent for the 7- to 10-year period to 9 percent at the 13-year point. Due to only 1 scrappage out of 143 in the age-12 risk set, however, the estimated hazard at year 12 is quite low, and a shift appears to occur at the 13-year point -- contrary to the predicted pattern. This shift can be attributed, however, to the smallness of the sample size and, given the estimated hazards in the surrounding years, the pattern of estimated hazards for private vehicles appears to be markedly different from the public sector.

The Kaplan-Meier estimates have the benefit of not imposing any structure upon the underlying baseline hazard. Since a major interest in this paper is how the hazard changes over time, these baseline estimates are of primary importance. They do not allow, however, for the control of observed heterogeneity in wage rates and operating conditions. Given the large number of private vehicles operating in the New York metropolitan area, for example, adverse operating conditions might have a major impact on observed private-sector scrappage. Accounting for this heterogeneity requires the introduction of parametric estimators discussed in the next two sections.

IV. The Fully Parametric Proportional Hazards Model

This section presents results from a fully parametric proportional hazards model that imposes the commonly used Weibull structure on the underlying baseline hazard.[13] The advantage of this approach is that it controls for covariants, such as wages and operating conditions, that affect scrappage. The drawback is that if the underlying baseline specification is incorrect, the estimates will be inconsistent. Due to the short four-year time period of the data, the beginning and end of most durations is not observed. Allowance is thus made for left- and right-censoring, respectively. The notation follows that used in Meyer (1988).

The hazard for vehicle i is assumed to be of the Cox (1972) proportional hazard form with baseline hazard $\lambda_0(t)$,

$$(7) \qquad \lambda_i(t) = \lambda_0(t)\exp\{z_i(t)\beta\}, \text{ i.e.}$$

$$(8) \qquad \lim_{h \to 0^+} \frac{\text{prob}\left[\, t+h > T_i \geq t \mid T_i \geq t \,\right]}{h} = \lambda_0(t)\exp\{z_i(t)\beta\},$$

where

T_i = the age vehicle i is scrapped,

$z_i(t)$ = a vector of time-dependent explanatory variables for vehicle i, and

β = a vector of parameters that is unknown.

The probability of a vehicle lasting until t+l given that it has lasted until t can then be written as a function of the hazard given that $z_i(t)$ is constant between t and t+1.

$$(9) \qquad P[\, T_i \geq t+1 \mid T_i \geq t \,] = \exp\left\{ -\int_t^{t+1} \lambda_0(u)\exp\{z_i(t)'\beta\}du \right\}$$

A Weibull baseline hazard of $\lambda_0(t) = \alpha t^{\alpha-1}$ is now imposed and equation (9) becomes

$$(10) \qquad P[\, T_i \geq t+1 \mid T_i \geq t \,] = \exp\left(-[\,(t+1)^{\alpha} - t^{\alpha}\,]\exp\{z_i(t)'\beta\} \right),$$

where

$$(11) \qquad h_i(t) = [\,(t+1)^{\alpha} - t^{\alpha}\,]\exp\{z_i(t)'\beta\}$$

is the average of the hazard over the interval [t,t+1). This specification results in the hazard function exhibiting positive (negative) age dependence as a is greater (less) than 1. The likelihood for a sample of N vehicles can be written as a function of the hazard and is shown in (12) with the log-likelihood given in (13).

$$(12) \quad l(\alpha,\beta) = \prod_{i=1}^{N} \left\{ \left[1-\exp\{-h_i(t)\} \right]^{\delta_i} \prod_{t=t_{oi}}^{k_i-1} \exp\{-h_i(t)\} \right\}$$

$$(13) \quad L(\alpha,\beta) = \sum_{i=1}^{N} \left\{ \delta_i \log\left[1-\exp\{-h_i(t)\} \right] - \sum_{t=t_{oi}}^{k_i-1} h_i(t) \right\},$$

where

δ_i = 1 if vehicle i is scrapped and

0 otherwise,

k_i = the age a vehicle is scrapped or censored, and

t_{oi} = the age at which vehicle i is initially observed.

Maximization of $L(\alpha,\beta)$ allows for consistent estimation of a and β if the Weibull specification is correct.

Descriptive statistics of the explanatory variables used in the estimation are given in table 4 for both the public and private properties. Included are the maintenance wage rate (WAGE) to control for the cost of maintenance, the average speed of operation (SPEED) to control for congestion, the ratio of vehicles needed at peak periods to total vehicles (SPARE) to control for utilization, and dummy variables for manufacturer types (FLX and AMG) to control for vehicles manufactured by Flxible Corporation and American Motors, respectively. (The remaining vehicles were manufactured by General Motors.)

Table 4
Descriptive Statistics:*
Public versus Private Transit Properties

Independent Variables	Public	Private
Number of Properties	101	11
WAGE ($/hour)	11.06 (3.15)	14.37 (5.38)
CITY	28/101	...
ATE	19/101	...
NY	2/101	7/11
SPEED (miles/hour)	13.22 (1.91)	11.12 (2.88)
SPARE (% spare at peak period)	31.11 (11.25)	25.09 (8.71)
CRASH (crashes per 1,000,000 miles)	41.25 (18.41)	59.79 (32.25)
CRIME (property crimes per 1,000 persons)	76.39 (24.21)	83.42 (50.30)

* Means, (standard deviations).

Source: Author's calculations.

Dummy variables are included for operation by city government (CITY) and operation by the private consulting firm American Transit Enterprises (ATE), which has a reputation for having well-maintained fleets. Finally, a dummy variable for operation in the New York metropolitan area (NY) is included to control for adverse conditions unique to this area. As over half of the observations of private vehicles occur in the NY area, this is an important control. The property crime rate (CRIME) and vehicle accident rate (CRASH) are also used to control for hazardous operating conditions. Finally the population density (DENSE) is included to measure congestion. Due to data limitations, most variables are assumed to be constant for each property over the 1982 to 1985 time period with the mean of the available values for the period used in the estimation.

The log likelihood function of equation (13) was maximized using the Berndt, Hall, Hall, Hausman (1974) algorithm; the inverse of the outer product of the gradients evaluated at the final parameter estimates was used as an estimate of the asymptotic variance-covariance matrix. Different starting values led to the same estimates, so the estimates seemed to be stable. The results are shown in table 5.

Equation 1 includes variables measuring wages and operating conditions, but does not control for differences between the public and

Table 5
Weibull Hazard Model Estimates*

	(1)	(2)
α	2.0574	2.0815
	(0.0041)	(0.0042)
Constant	-5.6442	-5.5499
	(0.0125)	(0.0131)
FLX	-0.6340	-0.4560
	(0.0083)	(0.0100)
AMG	-0.9629	-0.8159
	(0.0155)	(0.0166)
WAGE	-0.0124	-0.0250
	(0.0018)	(0.0020)
CITY	0.0306	0.1235
	(0.0188)	(0.0196)
ATE	0.5453	0.6036
	(0.0115)	(0.0123)
NY	-0.1713	-0.1824
	(0.0265)	(0.0285)
SPEED	-0.0169	0.0087
	(0.0037)	(0.0043)
SPARE	0.0045	0.0035
	(0.0005)	(0.0006)
CRASH	-0.0085	-0.0080
	(0.0003)	(0.0003)
CRIME	-0.0003	-0.0012
	(0.0002)	(0.0003)
DENSE	0.00025	0.00025
	(0.00001)	(0.000001)

Table 5 (cont.)
Weibull Hazard Model Estimates

	(1)	(2)
AGE8	---	-0.8374 (0.0256)
AGE9	---	-0.2262 (0.0166)
AGE10	---	-0.9792 (0.0284)
AGE11	---	-1.3032 (0.0546)
AGE12	---	-2.0550 (0.1298)
AGE13	---	-0.3141 (0.0152)
AGE14	---	-0.5308 (0.0247)
AGE15	---	0.2786 (0.0145)
Sample Size	**15,829**	15,829
Likelihood Value	**-10,241.41**	-10,220.99

***Estimated coefficents, (standard errors)**

Source: Author's calculations.

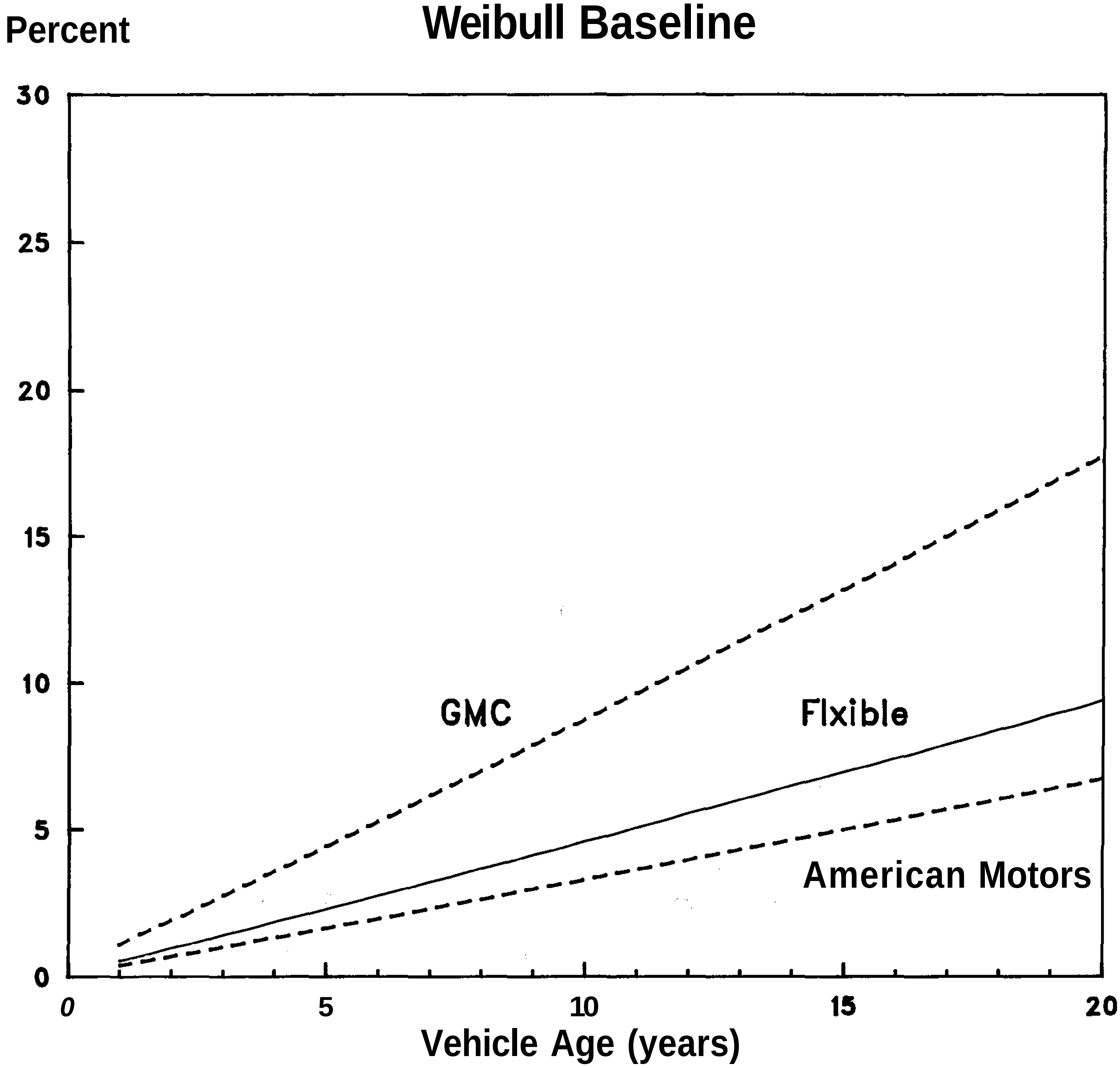
private sectors. The results, in general, are consistent with conventional wisdom in the transit industry. (Note that positive values indicate that the variable has a positive effect on scrappage). The baseline hazard shows a strongly positive time-dependence with a estimated at 2.0574. Evaluated at the means, this indicates that the baseline hazard rises steadily from under 2 percent for new vehicles to over 15 percent for vehicles over 18 years of age as shown in figure 3. (Using the estimated constant and estimated a in equation 11 yields this baseline hazard estimate since means were subtracted from the explanatory variables.) The estimated hazards for FLX and AMG-type buses, also shown on figure 3, are significantly lower than for the GMC buses. Since AMG vehicles were only manufactured between 1975 and 1978, however, this result should be treated with caution. The estimated hazard is higher in properties managed by ATE and lower in those managed by city governments. The variables controlling for operating conditions do not all have the expected signs. Operation in New York has a small negative effect, which is surprising, and areas with higher crime rates and accidents appear to have lower hazards. Higher speeds increase the hazard as does a higher spare ratio and a higher population density.

The estimated coefficient for WAGE has a negative sign, contrary to the prediction of the model, but is extremely small, suggesting that the level of maintenance wage has essentially no effect on scrappage decisions. A 10-percent increase in wages lowers the annual hazard by less than 0.2 percent. In specifications that do not include operating characteristics,

Figure 3

Scrappage Rate

Weibull Baseline



Source: Author's Calculations

such as DENSE, CRIME, and CRASH, the sign of WAGE is positive and significant -- but this appears to be due to the effects of operating conditions in high-wage areas such as New York.

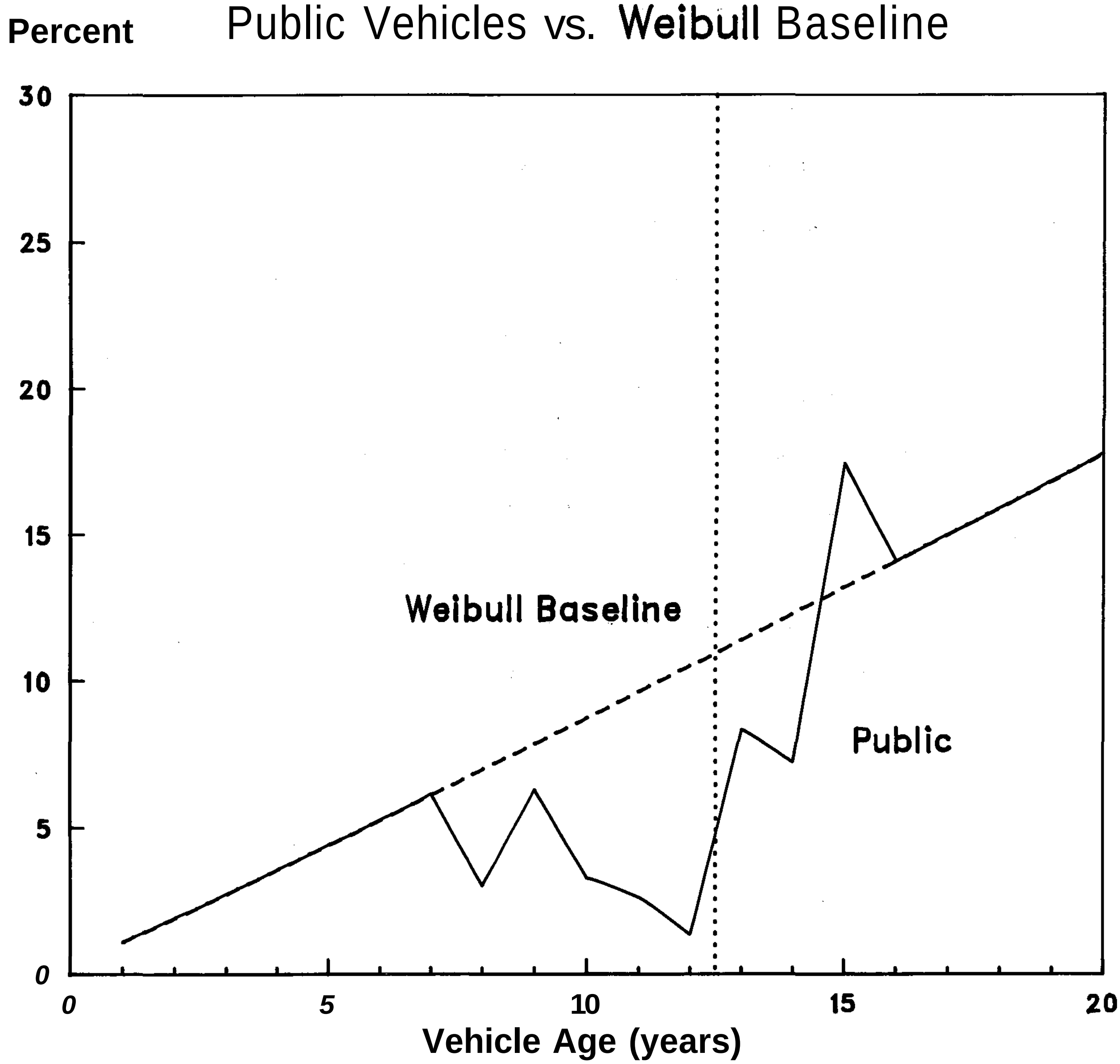
To explore how public scrappage might vary from this baseline, equation 2 includes dummy variables that equal one for public vehicles aged 8 through 15, AGE8 through AGE15, respectively. The results (shown in table 5 and figure 4) highlight the importance of the 13-year point in public behavior. In the five years preceding this point, public-sector scrappage is reduced by 9 percentage points below the baseline, then shifts up by 6 percentage points at the 13-year point and rises above the baseline by year 15. This shift suggests that the availability of federal subsidies are an important determinant of local scrappage decisions.

The drawback of using the Weibull specification to examine shifts in public versus private scrappage over time is readily apparent in that allowing public-sector scrappage to vary with the use of dummy variables imposes the Weibull structure on the private estimates. Given the extent that the public estimates diverge from the Weibull pattern when allowed to vary, this structure appears to be too constraining. In the next section, we will use a more flexible functional form to more reliably determine shifts in the underlying baseline hazards.

Figure 4

Scrappage Rate

Public Vehicles vs. Weibull Baseline



Source: Author's Calculations

V. The Semiparametric Hazard Estimator

The fully parametric hazard model allows for estimation of the impact of economic and environmental conditions on scrappage. These estimates are consistent, however, only if the specification of the baseline hazard is correct. For this reason, statisticians have argued for the nonparametric estimation of the baseline hazard. Meyer (1988), following Prentice and Gloekner (1978), presents a semiparametric hazard estimator (SPHE) that combines both approaches -- allowing for nonparametric estimation of the baseline hazard while permitting estimation of the impact of explanatory variables. We use this approach to assess the robustness and consistency of the Weibull estimates and to obtain a fuller analysis of the differences between the public- and private-sector baseline hazards.

As before, the hazard for vehicle i is of the proportional hazards form with baseline hazard $\lambda_0(t)$.

$$\lambda_i(t) = \lambda_0(t)\exp\{z_i(t)\beta\}, \tag{13}$$

where $0 \le t \le T < \infty$, and $\lambda_0(t)$ and β are unknown. No structure, however, is imposed on $\lambda_0(t)$. Meyer notes that the average of the hazard over the interval $[t,t+1)$ is

$$h_i(t) = \int_t^{t+1} \lambda_0(u)\exp\{z_i(t)\beta\}du \tag{14}$$

and makes the substitution

$$(15) \qquad \gamma(t) = \ln \int_t^{t+1} \lambda_0(u)du$$

so that $h_i(t) = \exp\{\gamma(t) + z_i(t)\beta\}$. The log-likelihood is now

$$(16) \quad L(\gamma,\beta) = \sum_{i=1}^{N} \left\{ \delta_i \log\left[1-\exp\{-h_i(t)\} \right] - \sum_{t=t_{oi}}^{k_i-1} h_i(t) \right\}.$$

Maximization of $L(\gamma,\beta)$ allows consistent estimation of β and of $\gamma(t)$, $(t=0,1, \ldots, T-1)$. Equation 1 was reestimated with the same β but with 20 $\gamma(t)$ instead of the Weibull baseline hazard. (Note that the constant is omitted from β in the SPHE.) The results are shown under equation 3 in table 6 with the estimated $\gamma(t)$'s reported in table 7.

In general, the SPHE appears to dominate the fully parametric estimator for our purposes. A likelihood ratio test rejects the null hypothesis of a Weibull baseline, indicating that the Weibull model is misspecified. The chi-square statistic with 18 degrees of freedom is 1118.28 versus a critical value at the .01 level of 34.8. This strong rejection is not surprising given the extent that the public-sector estimates in section 4 diverged from the Weibull structure. While many of the estimated coefficients for the operating and explanatory variable retain the same sign and magnitude,'the estimated coefficients for CITY,

Table 6
Semiparametric Hazard Model Estimates*

	(3)	(4)
α	---	---
Constant	---	---
FLX	-0.2459 (0.0106)	-0.2886 (0.0119)
AMG	-0.2993 (0.0190)	-0.3026 (0.0207)
WAGE	-0.0270 (0.0021)	-0.0189 (0.0022)
CITY	0.2646 (0.0224)	0.2355 (0.0221)
ATE	0.6600 (0.0130)	0.6840 (0.0146)
NY	0.1405 (0.0321)	0.7494 (0.3225)
SPEED	0.0093 (0.0047)	0.0069 (0.0047)
SPARE	0.0056 (0.0006)	0.0064 (0.0006)
CRASH	-0.0098 (0.0004)	-0.0146 (0.0004)
CRIME	0.0020 (0.0003)	0.0037 (0.0003)
DENSE	0.00023 (0.000007)	0.00027 (0.000007)
AGE8	---	0.8587 (0.0284)

Table 6 (cont.)
Semiparametric Hazard Model Estimates

	(3)	(4)
AGE9	---	0.3656 (0.0281)
AGE10	---	0.6250 (0.0436)
AGE11	---	0.4124 (0.0244)
AGE12	---	0.8412 (0.0267)
AGE13	---	0.9172 (0.1083)
AGE14	---	1.1774 (0.1346)
AGE15	---	1.3084 (0.0992)
AGE16	---	1.7929 (0.0320)
AGE17	---	0.0835 (0.0451)
AGE18	---	1.0750 (0.0681)
AGE19	---	-0.1512 (0.0525)
AGE20	---	-0.2459 (0.0672)
Sample Size	15,829	15,829
Likelihood Value	-9,682.27	-9,499.12

*Estimated coefficents, (standard errors). Baseline hazard estimates shown on Table 7.

Source: Author's calculations.

Table 7
Semiparametric Hazard Model:Baseline Estimates*

Year	(3)	(4)
1	-4.01 (0.03)	-4.07 (0.03)
2	-3.63 (0.01)	-3.69 (0.02)
3	-3.64 (0.02)	-3.73 (0.02)
4	-4.49 (0.04)	-4.58 (0.04)
5	-4.56 (0.05)	-4.63 (0.05)
6	-3.40 (0.02)	-3.49 (0.02)
7	-3.97 (0.03)	-4.02 (0.03)
8	-3.72 (0.03)	-4.59 (0.04)
9	-2.96 (0.02)	-3.59 (0.04)
10	-3.54 (0.03)	-4.23 (0.06)
11	-3.60 (0.05)	-4.56 (0.06)
12	-4.45 (0.13)	-5.25 (0.13)
13	-2.51 (0.02)	-3.37 (0.11)
14	-2.68 (0.02)	-3.80 (0.13)

Table 7 (cont.)
Semiparametric Hazard Model:Baseline **Estimates***

	(3)	(4)
15	-1.81	-3.27
	(0.01)	(0.10)
16	-1.90	-3.60
	(0.01)	(0.04)
17	-1.90	-2.20
	(0.02)	(0.04)
18	-1.31	-2.44
	(0.01)	(0.07)
19	-1.18	-1.42
	(0.01)	(0.05)
20	-1.41	-1.34
	(0.02)	(0.07)

***Estimated** $\gamma(t)$, **(standard errors)**

Source: Author's calculations.

NY, and CRIME switch signs from negative to positive. This is reassuring given that these signs, especially for NY, are more in line with the conventional wisdom of the transit industry. The estimated coefficient of WAGE remains negative but is highly inelastic.

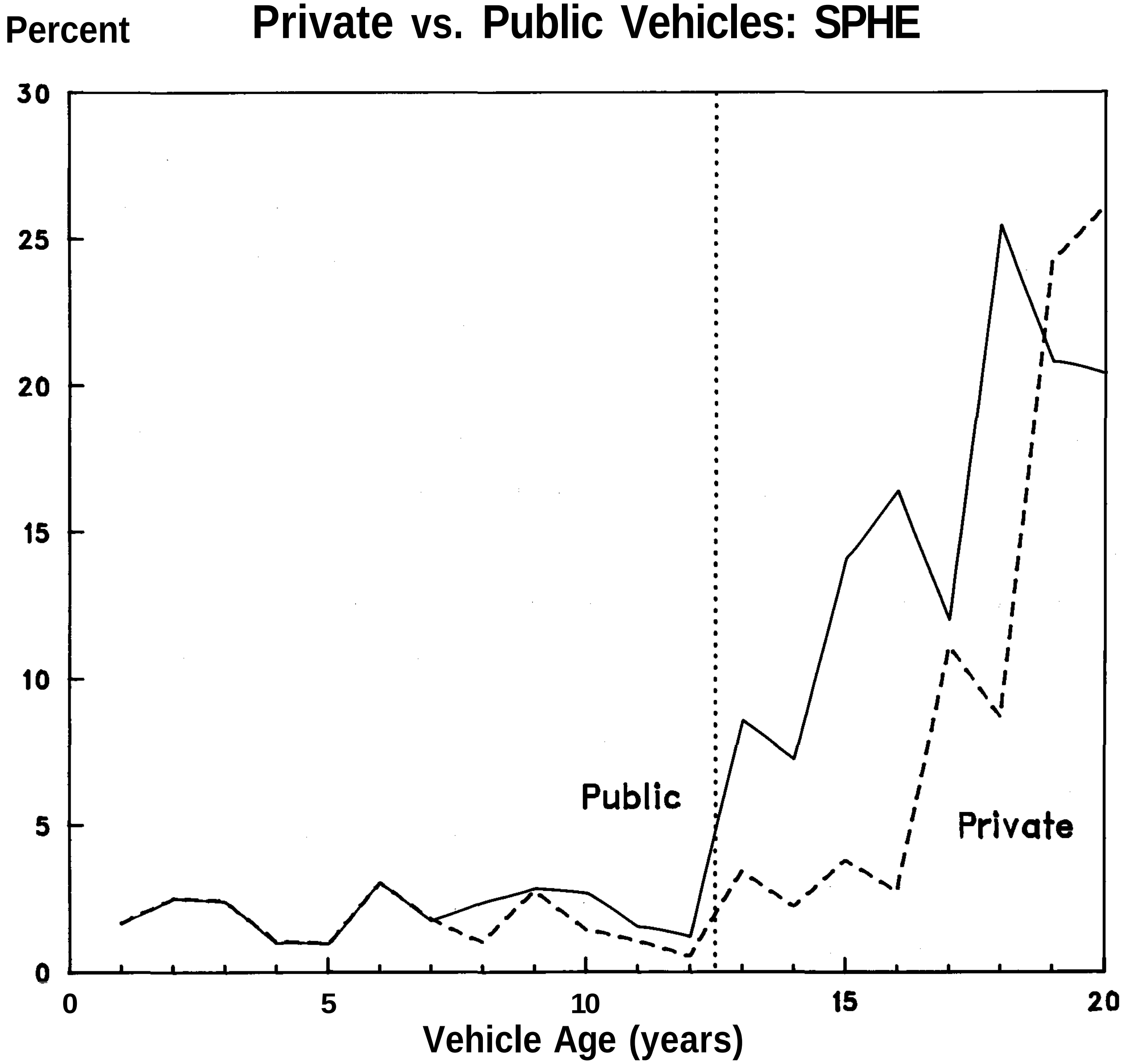
More importantly, use of the SPHE permits a much fuller analysis of differences in the baseline hazards between the public and private sectors. Equation 3 was reestimated with dummy variables to account for differences in public- and private-sector scrappage from age 8 through age 20.[14] These results are given in equation 4 with the corresponding baseline hazards shown in figure 5. The impact of the grant structure on public-sector scrappage is readily apparent. While the private-sector baseline remains under 10 percent until year 16 and then rises steadily through year 20, the public-sector baseline takes a distinct and significant jump at the 13-year point from 4 percent to over 12 percent, twice that of the private sector. Scrappage then rises to over 25 percent for 15- and 16-year-old vehicles and remains above the private sector until year 19. The distinct difference in scrappage rates can be attributed to the availability of federal grants.

An alternative approach to examining public and private scrappage is to look at the survivor functions for the two sectors. The survivor function is defined as the percentage of vehicles of a given vintage that survive to a given age and is composed of the estimated hazard components $\hat{\lambda}_1,\ldots\ldots,\hat{\lambda}_k$ at $t_1,\ldots\ldots,t_k$ as follows:

Figure 5

Scrappage Rate

Private vs. Public Vehicles: SPHE



Source: Author's Calculations

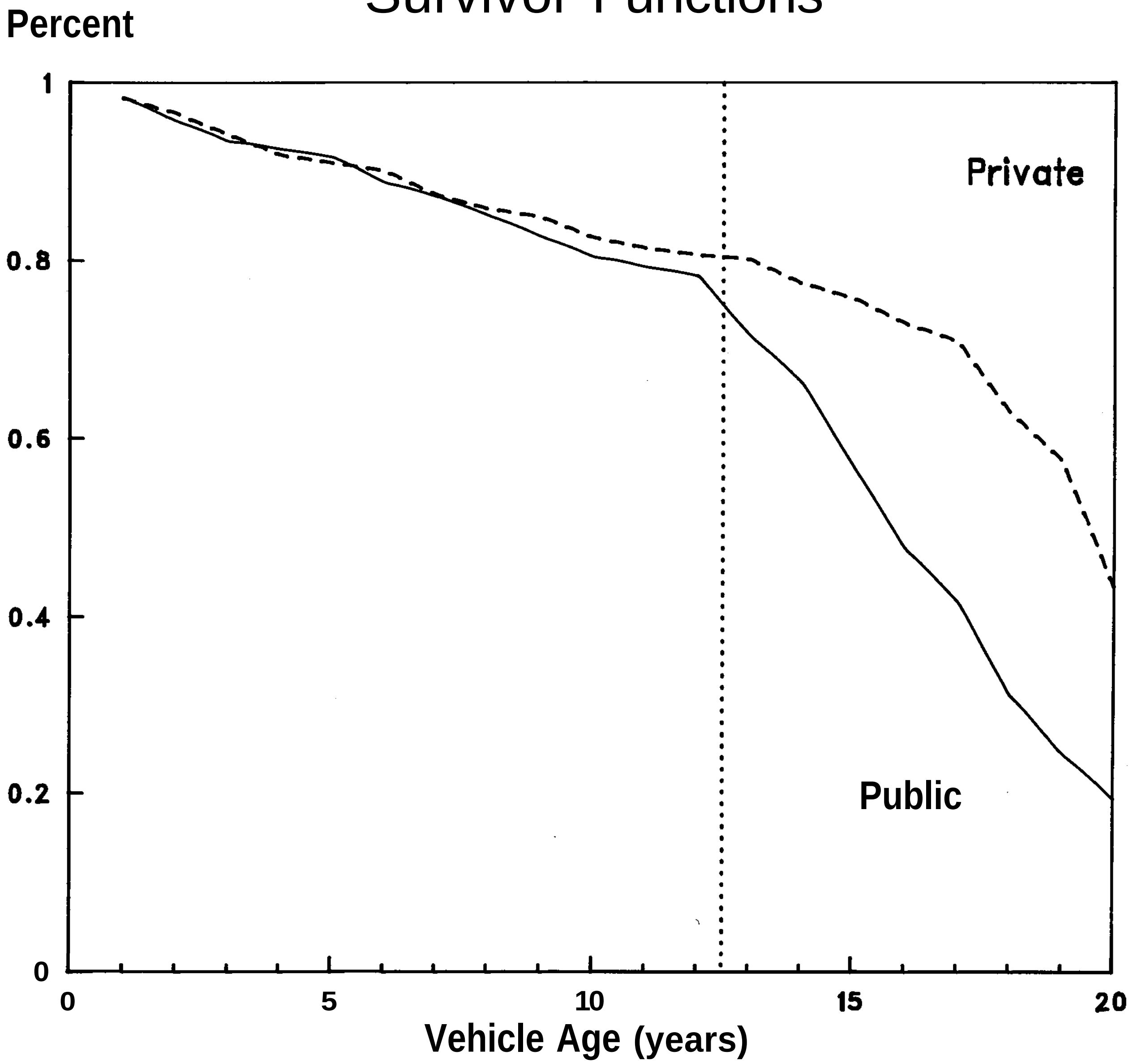
(16) $$\hat{F}(t_k) = \prod_{i=1}^{k} \left(1 - \hat{\lambda}_i\right)$$

for k = 1,....20. The survivor function estimates calculated from the estimated baselines are shown in figure 6 and further emphasize the difference between public and private scrappage policies. The two functions track closely through year 12, then diverge as public scrappage sharply increases. Again, this shift in the survivor function at the 13-year point can be attributed to the sudden availability of federal subsidies. By age 16 only 47 percent of the public vehicles survive as opposed to 73 percent for private vehicles. At age 20, 45 percent of private vehicles are still estimated to be in operation versus 20 percent for the public sector.

As an example of the difference in cost between the two scrappage policies, consider a public transit property that requires 500 vehicles to meet demand. With the public survivor function estimated above, this would require new vehicle purchases of 35 per year. The average age of the fleet would be 8.6 years. Given the private-sector survivor function, however, only 31 new vehicles a year would be required to maintain a 500-vehicle fleet. This reduction in new purchases of four vehicles per year at a price of $150,000 per vehicle results in annual savings of $600,000. The average fleet age would rise to 9.6 years. An older fleet, however, entails higher maintenance expenses. Cromwell (1988) demonstrates that private transit properties devote significantly more resources to maintenance. Using the public/private differential together with

Figure 6

Survivor Functions



Source: Author's Calculations

cross-state variation in capital subsidy policies, an elasticity of maintenance with respect to capital subsidy rates of -0.158 is estimated with a standard error of 0.088. This implies that the 80 percent federal capital subsidy reduces public sector maintenance by 12.8 percent. For an average public property with 500 vehicles, such a percentage increase results in increased costs of $920,000.[15] Taking a one-standard-error range yields an estimate of $410,000 to $1,430,000, bracketing the savings from reduced vehicle purchases. These higher maintenance expenses thus potentially more than offset the savings from reduced replacement investment, and if attributable to higher vehicle age, suggest that the change in total costs from an increase in average vehicle age would be small. If there are unobserved benefits from increased maintenance, such as increased cleanliness and reliability of service, however, the net cost of the additional maintenance would be smaller than the estimates above.[16]

The consistently lower survival rate of publicly owned vehicles after the availability of federal funds is direct evidence that federal capital grants reduce equipment life in the local public sector. It suggests that federal grant policies that subsidize the purchase of new capital but ignore the maintenance of existing capital result in the increased deterioration of public infrastructure. The magnitude of savings for the transit industry from a shift in policies, however, may be small if maintenance expenses offset reduced vehicle expenditures.

VI. Conclusion

This paper examines capital policies in the public and private sector through analysis of the scrappage decisions of local mass transit providers. It shows that the structure of federal grants has a direct impact on scrappage rates that leads to shorter equipment life in the local public sector. The analysis applies hazard modeling techniques previously used for examination of unemployment duration and in the biometrics literature. The results show the advantage of the semiparametric hazard estimator (SPHE), which allows flexibility in comparing underlying baseline hazards across time and between sectors. In particular, the commonly used Weibull approach, which imposes a restrictive structure on the baseline hazard, is shown to be inconsistent for this application.

Federal grant policies for mass transit subsidize the replacement of transit vehicles at a matching rate of 80 percent once these vehicles turn 13 years old. Using the SPHE to compare scrappage decisions and equipment life in the public sectors shows that the availability of these grants results in shorter equipment life in local public transit properties. While the estimates suggest that the net costs in local mass transit for increased bus replacement is small, changes in local behavior are induced by distortionary grant policies and should be considered when designing federal infrastructure policy. Policies that emphasize new capital construction, as opposed to the maintenance of existing infrastructure, may be counterproductive.

Endnotes

1. A good account of the "crisis" is given in Leonard (1985).

2. See Cromwell (1988).

3. For surveys of this literature, see Pierskall and Voelker (1976), and Sherif and Smith (1981).

4. The model is an extension of that used in Jorgenson, McCall, and Radner (1967) and in Nickell (1978). For further discussion of maintenance and depreciation, see Cromwell (1988).

5. See UMTA (1983).

6. Figure cited is as of the 1983 report year.

7. See UMTA (1985).

8. See Touche Ross (1986).

9. Solicitations for bids for used buses were found in back issues of <u>Passenger Transport</u> from January 1987 through June 1988.

10. Privately owned companies were identified using UMTA (1986).

11. See Kaplan and Meier (1958).

12. The standard errors were calculated using a suggestion in Kalbfleish and Prentice (1980).

13. This specification is used by numerous authors. See Lancaster (1979) and Katz (1986).

14. The baselines were constrained to equal one another for ages 1 through 8 to reduce computation time. Analysis of the Kaplan-Meier estimates suggests little difference in scrappage rates during this period.

15. This estimate assumes average vehicle mileage of 27,500 per year and maintenance expenses of $0.53 per mile. The mileage estimate is the average of mileage from the 1983, 1984 and 1985 fleet data. The cost-per-mile estimate is a 1984 average from Cromwell (1988), table 2.

16. For further discussion of maintenance issues, see Cromwell (1988).

References

Berndt, E.R., B.H. Hall, R.E. Hall, and J.A. Hausman (1974): "Estimation and Inference in Non-Linear Structural Models," Annals of Economic and Social Measurement, 3(4), 653-665.

Cox, D. 'R.(1972): "Regression Models and Life-Tables," Journal of the Royal Statistical Societv B, 34, 187-202.

Cromwell, Brian A. (1988): "The Impact of Capital Grants on Maintenance in the Local Public Sector," Federal Reserve Bank of Cleveland, mimeo.

Jorgenson, D.W., J.J. McCall, and R. Radner (1967): Optimal Replacement Policv. Chicago: Rand McNally & Co.

Kalbfleisch, J., and R. Prentice (1980): Statistical Analvsis of Failure Time Data. New York: Wiley.

Kaplan, J.D. and P. Meier (1958): "Nonparametric Estimation from Incomplete Observations." J. Am. Stat. Assoc., 53, 457-481.

Katz, L. (1986): "Layoffs, Recall and the Duration of Unemployment," NBER Working Paper Number 1825.

Lancaster, T. (1979): "Econometric Methods for the Duration of Unemployment," Econometrica, 47, 939-956.

Leonard, Herman B. (1985): Checks Unbalanced: The Ouiet Side of Public Spending. New York: Basic Books.

Meyer, B. (1988): "Semiparametric Estimation of Hazard Models", mimeo, Northwestern University.

Nickell, S. J. (1978): The Investment Decisions of Firms. Cambridge University Press.

Pierskall, W.P. and J.A. Voelker (1976): "A Survey of Maintenance Models: The Control and Surveillance of Deteriorating systems," Naval Research Logistics Quarterly, 23, 353-388.

Prentice, R. and L. Gloeckler (1978): "Regression Analysis of Grouped Survival Data with Application to Breast Cancer Data," Biometrics, 34, 57-67.

Sherif, Y.S. and M.L. Smith (1981): "Optimal Maintenance Models for Systems Subject to Failure- A Review," Naval Research Logistics Ouarterlv, 32,47-74.

Touche Ross & Co. (1986): Assessment of Transit Industry

Capital Investment Practices. prepared for U.S. Department of Transportation, Urban Mass Transportation Administration.

Urban Mass Transportation Administration, U.S. Deparment of Transportation (December 1984): National Urban Mass Transvortation Statistics, 1983 Section 15 Annual Report, Report No. UMTA-MA-06-107-85-1.

Urban Mass Transportation Administration, U.S. Department of Transportation (June 1985): Circular 9030.1

Urban Mass Transportation Administration, U.S. Department of Transportation (August 1986): A Directory of Urban Public Transportation Service.