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Fares, Service Levels, and Demographics: What Determines Commuter Rail Ridership in the Long Run?[1]

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Using panel data covering a 13-year period, this paper examines the roles of transportation policy and demographic changes in determining rail ridership. The paper presents a model which allows identification of long-run responses of ridership to changes in prices and service independently of exogenous shocks to ridership caused by demographic factors. Long-run price and service elasticities are estimated to be almost twice as large as short-run elasticities. After controlling for transportation prices and service levels, demographic variables contribute little to explaining residual differences in ridership. To the extent that demographic changes are driven by transportation variables, these effects are captured in the estimated long-run elasticities. © 1997 Academic Press

In recent years, economists have focused on the travel choices made by individuals, rather than the demand for transit in specific neighborhoods or communities. Analyses of public transportation demand typically are based on the random utility model pioneered by McFadden [8] and empirically implemented within the discrete choice framework. Elasticity estimates from these analyses are short run; they yield estimates of demand conditional on a previously determined set of choices regarding residential and employment location as well as investment in private transportation.

Yet from the point of view of a policymaker deciding whether to provide fixed-rail service to a particular community or of a transit authority trying to decide how much service to provide on an existing route, the current and expected future aggregate demand of the community is most impor-

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tant. Of course, a community's aggregate transit demand is simply the sum of individual mode choices, but demographic factors influencing transit ridership, such as the size of a community's population, the set destinations of the population, and the level of investment in private transportation, are all likely to be affected by transportation policy choices.[2] The extent to which a community's demographic characteristics are shaped by transportation policy, as opposed to being the result of other exogenous forces, has received relatively little analysis.

Failure to recognize the endogeneity of location and auto-ownership decisions can lead to poor policy choices. Most obviously, estimates of long-run elasticities of demand with respect to price and quality of service are likely to be understated, so that fare increases and service reductions may have unexpectedly negative long-run consequences for ridership and revenue [13]. Less obvious are the adverse long-run effects of misallocating subsidies across intraregional markets. High subsidies for service to high-cost locations may undermine the competitive advantage of locations that are less costly to serve, reducing the long-run viability of transit service and communities dependent on transit service [16].

Recognizing that mode choice is part of a larger set of decisions, a number of researchers (Lerman [7], Anas [1], and Train [12], for example) have analyzed models of joint mode, residential location, and car ownership choices. Waddell [17] examines the joint choice of residential and employment location. Because they incorporate the effects of changing transportation policies on location and car ownership, these models, in theory, yield long-run estimates of demand at the individual and community level.

Aside from the well-known difficulty of delineating an appropriate set of joint mode–location–car ownership choices, at least three other problems limit the usefulness of these models for estimating long-run travel demands. One problem arises from the difference in the relative frequency of choice of travel mode when compared with the frequency with which location choice and car purchases are made. The high frequency of mode choice allows rapid adjustment to changes in price and service, but the

[2] Voith [14] provides evidence that transportation characteristics affect the composition of employment destinations of a residential community, as well as the level of car ownership. In particular, he found that suburban communities in the Philadelphia metropolitan area with high-quality commuter rail service to the central business district (CBD) tend to have a high fraction of people working in the CBD when compared to otherwise similar communities. In addition, residents of these communities tend to own fewer cars, given their income levels. In a recent study of the Massachusetts Bay Transportation Authority (MBTA), Gomez-Ibanez [5] found that demographic changes had large effects on MBTA ridership over the past 20 years. Gomez-Ibanez did not, however, analyze the extent to which transportation policies affected the pattern of demographic change.

infrequent choices of job location and residence and auto ownership do not allow rapid adjustment to a new equilibrium. Thus, changes in the relative prices and qualities of transportation modes will have consequences that are realized only after enough time has elapsed for longer-run location and private transportation choices to be made and may not be estimable from a single cross section.

Another, more serious problem is that the prices of alternative locations for residence and employment are not independent of the prices and qualities of transportation alternatives.[3] Thus, the delineation of a discrete set of joint alternatives with known prices is problematic, making estimation of the long-run consequences of changes in transportation policy difficult to assess within the discrete choice framework.

The third difficulty in using the discrete choice framework arises from the fact that the number of potential rail riders in a particular community changes over time, making it difficult to empirically specify estimation equations in terms of modal shares. As the size of employment in the CBD changes, for example, the number of potential train riders in a given residential community is likely to change. Without time series data on the number of people in each community working in the CBD, we cannot reasonably specify CBD market shares for train and auto travel.

Voith [13] takes an alternative approach to investigate a community's transit demand. Using a panel data set on commuter rail ridership, fares, and service to 129 communities for 12 time periods between 1978 and 1986, Voith estimates a reduced-form, fixed-effects model of ridership at the community level, which yields short- and long-run elasticities of demand with respect to changes in price and service. He finds that long-run elasticities are more than two-and-one-half times as large as short-run elasticities.

Using station level panel data to estimate long-run price and service elasticities introduces a different type of problem: transit authorities may adjust price and service levels in response to exogenous changes in demographics as well as induce demographic change through their policies. Correlations between service levels and ridership, for example, might arise from authorities' response to increased ridership resulting from exogenous demographic change, as opposed to higher service levels inducing higher

[3] In fact, the basic urban models are those of land prices being determined by transportation costs. A broad empirical literature documents the effects of transportation systems on land prices. See Boyce *et al*. [3], Damm *et al*. [4], Voith [14], and Voith [15] for examples. Anas and Duann [2] have attempted to address this issue by embedding a travel demand model in a large urban simulation model which determines the effects of transportation system changes on land values and use. The model is simulated recursively to estimate the long-run impacts of transportation policy changes, based on transportation and land use equations estimated from a single cross section.

ridership. To obtain unbiased long-run elasticity estimates we need to distinguish between price–service–ridership correlations generated by a transit authority's reaction to exogenous changes in demographics and ridership changes resulting from innovations in transit authority policy.

The purpose of this paper is to extend the Voith [13] analysis in four ways. First, 5 additional years of data, as well as more detailed service, subsidy, and cost data, have been added, which allows reestimation of the original model as well as evaluation of more complex models. Second, we develop a simple model of supply and demand for commuter rail service, which allows identification of the long-run response of ridership to changes in prices and service independently of exogenous shocks to ridership caused by demographic or other factors. Third, we investigate the pattern of fixed effects across communities in an attempt to explain large average differences in ridership across communities. Fourth, we examine the sources of differential changes in ridership across stations to determine the relative importance of exogenous changes in demographics as opposed to changes that can be explained by differences in policy. Our findings can be summarized as follows:

(1) OLS fixed-effects estimations using the enlarged sample (1978–1991) yield similar coefficients to those from the 1978–1986 sample. In the larger sample, the effects of off-peak service, speed, and price are somewhat smaller than in the shorter sample, while the effect of peak service is a bit larger. The geometric lag parameter, which determines relative magnitudes of the long- and short-run effects, is about 20% larger in the full sample. Using the full sample OLS estimations of a model specified in first differences yields estimates that are comparable to the fixed-effects estimation. The impacts of peak service levels, however, are about half the magnitude of the fixed-effects estimations. Both the fixed-effects model and the first difference model imply long-run impacts that are roughly twice as large as short-run effects.

(2) Two-stage least-square estimations of the full model, which control for the endogeneity of price and service levels, yield qualitatively similar results. In the fixed-effects specification, the primary difference from the OLS estimations is that the geometric lag parameter is estimated to be about 20% smaller, implying smaller long-run effects. For the first difference model, the coefficients on peak and off-peak service frequency were somewhat smaller than the OLS estimates. The short-run point estimate of the impact of peak service level is not statistically significant, although the long-run effect of peak service frequency remains significant.

(3) After controlling for changing price and service characteristics, neither the differences in ridership levels nor the differences in rates of change of ridership across stations are significantly affected by demo-

graphic variables. The results suggest that most of the effect of demographic variables on ridership is induced by transportation policy and is captured in the estimated parameters of the transportation variables.

I. DATA

The panel data set used in Voith [13] is expanded by adding 5 additional years, increasing the information on service quality, including annual cost, subsidy and deficit data, and adding demographic data from the 1980 and 1990 censuses. The data cover 118 of 165 stations on the Southeastern Pennsylvania Transportation Authority (SEPTA) commuter rail system on an annual basis from 1978 through 1991.[4] As in Voith [13], there are station level data on ridership, fares, peak and off-peak service levels, average speed, and automobile operation and parking costs.

We also collected data on other factors that affect the relative attractiveness of train service not captured by the variables above. Through interviews with SEPTA personnel, we have identified on a station-by-station basis, for each time period, four conditions that may affect ridership: reliability, service interruptions, changes in transit competition, and changes in auto competition.[5] Each of these qualitative variables are scaled so that they take on a value of -1 if a particular event (such as unreliable service because of a track repair project) would have reduced ridership at a station or 1 if the event (such as a highway construction project causing road congestion) would have increased ridership at a station.

Table 1 displays means for ridership, price, and service characteristics as well as cost, subsidy, and deficit data by year and for the overall sample. The ridership figures are for inbound boardings and the number of peak

[4] SEPTA provides commuter rail service throughout the city of Philadelphia and four suburban counties in Pennsylvania. Stations were generally included in the sample if they had continuous service over the sample period. Seven additional stations along a refurbished subway line, three stations with no off-peak service, and three stations with periods of no ridership were excluded as well. There are no ridership data available for 1983, a year in which there was a 3-month hiatus in service because of a strike. Because I had fall of 1992 ridership and spring of 1994 ridership, effectively I have two cross sections for 3 years. I have treated them as if they are annual.

[5] The reliability variable captures the extent to which the actual train service matches the scheduled service. The service interruption variable reflects whether the ridership was affected by an interruption of service during the period (which might reduce current ridership) or whether another competing line experienced a shutdown (which would increase ridership). Some of the commuter rail lines have competition from other transit services, which, to the extent that these services either improved or on the other hand were eliminated, could affect commuter rail ridership and hence a measure of transit competition was included. Finally, we attempted to capture the effects of changing highway competition on ridership. We identified changes in the quality of the auto competition such as congestion due to highway construction or faster auto commutes because of increased highway capacity.

TABLE 1
Means by Observation Period

Period	Riders per station	Peak trains	Off-peak trains	Speed (MPH)	Round-trip price	Auto cost (variable)	Cost per vehicle mile	Subsidy (millions)	Deficit (millions)	Employment (thousands)
1978	407	7.8	20.3	25.1	4.68	10.96	7.87	270.3	2.09	797.5
1979	424	7.8	20.3	24.1	4.63	9.95	7.82	262.6	11.64	792.1
1980	395	7.9	20.5	24.2	5.81	10.57	7.60	263.5	13.07	780.1
1981	333	6.7	15.0	24.5	6.56	9.80	8.09	240.8	6.74	764.3
1982	324	6.7	15.0	24.7	6.19	9.13	8.39	246.6	25.13	747.9
1984[a]	230	7.4	17.3	24.6	5.74	8.95	7.85	266.3	28.06	750.8
1985	293	7.5	18.4	23.9	6.05	9.50	7.93	251.4	0.51	759.5
1986	357	7.6	19.0	23.8	6.64	9.11	8.67	250.4	1.86	762.1
1987	330	7.7	18.6	23.6	6.41	9.01	8.97	247.1	2.04	777.3
1988	330	7.7	19.3	23.7	6.16	9.66	8.72	259.9	0.58	771.4
1989	297	7.5	19.8	24.0	6.80	10.01	8.45	285.6	0.22	753.7
1990	291	7.6	19.7	23.5	6.97	10.52	8.34	288.6	2.92	727.4
1991	276	7.5	20.0	23.7	6.69	9.91	8.15	282.3	0.70	712.6
Average	330	7.5	18.7	24.1	6.10	9.77	8.22	262.7	7.35	761.3

[a] No ridership survey was conducted in 1983.

and off-peak trains are inbound trips. The speed given is for the typical peak-hour train. All dollar amounts are in real terms with 1991 as the base year. The price of a train is the round-trip fare. The cost of an auto trip includes the operating cost per mile times the number of miles in a round trip plus the cost of parking. Subsidies include state, local, and federal operating subsidies for the entire SEPTA system.[6] Costs are the expenses incurred per vehicle mile of operation, again for the entire SEPTA system. Deficits are the excess of expenses over revenues plus subsidies for the entire system. Finally, we have included the level of Philadelphia employment as a measure of the overall size of the potential destination market.

In aggregate, ridership fluctuated considerably during the sample period. From 1979 to 1982 ridership fell by 23.6% as service levels were reduced 23.2%, real prices rose 33.7%, and Philadelphia employment fell 5.6%. Real unit costs per vehicle mile were rising (7.3%) and subsidies were falling (6.1%) during this period. Ridership then plummeted to slightly more than half of the 1979 level by 1984 after an extended strike in 1983. In the subsequent 2 years, ridership rebounded 55.1%, almost back to 1980 levels; as service frequency increased, real prices were reduced (in 1984 and 1985 compared with 1982 levels), and Philadelphia employment increased slightly (1.5%).

The additional 5 years of data (1987−1991) beyond the Voith [13] analysis show ridership declines of 22.8% from 1986 to 1991. At the same

[6] Roughly one-third of SEPTA subsidies have typically been used for the commuter rail system.

TABLE 2
Ridership Levels

Ridership	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Total
A. Ridership Levels by Zone						
Mean	151.8	327.5	399.3	343.2	298.2	329.8
Standard deviation	163.4	237.2	330.2	311.2	303.6	284.9
Maximum	741	1277	1798	1517	1100	1798
Minimum	2	13	3	9	13	2
Number of stations	12	47	34	15	10	118
B. Percentage Change in Ridership 1978–1991 by Zone						
Mean	−61.5	−43.5	10.1	0.1	2.5	−20.5
Standard deviation	23.6	24.1	120.0	73.0	57.9	77.4
Maximum	−2.1	23.8	536.8	200.0	109.6	536.8
Minimum	−91.7	−77.5	−61.5	−67.3	−60.7	−91.7
Number of stations	12	47	34	15	10	118

time there were only slight changes in average service levels and real fares. There were two intervening years, however, 1989 and 1990, with cumulative price increases of 13.1%. The ridership drop from 1986 to 1991 is large relative to the drop in Philadelphia employment, which was slightly more than 6.5%.[7] Subsidies increased rapidly (12.7%) while unit costs actually fell 6.1%.

There are extremely large variations in ridership and considerable differences in ridership growth between stations. Table 2A displays the mean and standard deviation of ridership overall and by zone as well as the highest and lowest ridership station in each zone. (Service on the SEPTA system is divided into fare zones, with each successive zone farther from the CBD.) Table 2B shows the corresponding data for ridership growth from 1978 to 1991. A key question is whether the large variation in ridership and ridership growth across stations is the result of service characteristics inducing high or low ridership or whether other factors, such as differences in the levels or growth rates of income, population, car ownership, etc., are responsible for the cross-station variation.

There are distinct spatial patterns of change in fares and ridership over the entire sample period, 1978–1991, that are similar to those reported in Voith [13]. Ridership fell by 55.5% in fare zone 1 (stations closest to the CBD) but only 8.6% in fare zone 5 (Table 3A). Fares in zone 1 increased 63.3%, while those in zone 5 increased by 10.6%. Peak and off-peak

[7] SEPTA estimates that nearly 80% of its riders are commuters bound for center city Philadelphia [9]. Declining employment may reduce commuter rail use more than proportionately because it may also lower road congestion, increasing the relative attractiveness of auto commutes.

TABLE 3

Percentage Changes in Means: Selected Variables by Zone

Variable	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
		A. 1978–1991			
Riders per station	−55.5	−43.7	−23.2	−18.7	−8.6
Number of peak trains	−10.6	−13.1	0.7	10.3	5.0
Number of off-peak trains	−23.2	−15.5	11.7	23.7	24.6
Round-trip fare	63.3	72.1	33.1	29.1	10.6
		B. 1978–1982			
Riders per station	−24.9	−21.3	−18.0	−19.1	−23.1
Number of peak trains	−14.1	−17.8	−12.4	−11.1	−18.3
Number of off-peak trains	−37.0	−27.0	−23.4	−17.2	−33.3
Round-trip fare	23.1	48.5	25.3	29.0	22.4
		C. 1984–1991			
Riders per station	−17.7	8.0	33.8	15.5	56.9
Number of peak trains	−3.8	−2.4	3.3	11.2	5.0
Number of off-peak trains	6.6	7.8	25.1	20.4	14.7
Round-trip fare	42.8	25.5	14.4	7.7	−2.7

service fell by 10.6% and 23.2%, respectively, in zone 1, but increased by 5.0% and 24.6%, respectively, in zone 5. As a rule, ridership fell less, fares increased less rapidly, and service increased more with each successive fare zone.

Interestingly, this pattern of differential change did not take place until SEPTA took over the service from Conrail in 1983. In the period 1978–1982, ridership declines were relatively uniform across zones as were changes in price and service levels (Table 3B). Only in the latter period did the spatial pattern emerge (Table 3C). One interesting question is the extent to which the declines in ridership in the close-in zones are the result of the policies regarding price and service levels as opposed to changes in demographic factors.

II. ANALYTICAL FRAMEWORK

To distinguish the effects of changes in price and service levels on ridership from a transit authority's response to exogenous changes in ridership we need to construct an identified model of transit supply and demand at the community level.

Demand

Following Voith [13], the number of trips taken from station j at time t, R^{jt}, is assumed to depend on the fare at each station, j, in year t, p_{o}^{jt}, the price of the same trip by auto, p_{a}^{jt}, the train service attributes, A_{o}^{jt}, the attributes of the same trip by auto, A_{a}^{jt}, and the size of the potential market, ϕ^{jt}.[8] ϕ^{jt}, in turn, depends on the distribution of destinations, D^{jt}, car ownership, K^{jt}, income, Y^{jt}, and population, N^{jt}, in community j.

$$R^{jt} = H\left(p_{\mathrm{o}}^{jt}, p_{\mathrm{a}}^{jt}, A_{\mathrm{o}}^{jt}, A_{\mathrm{a}}^{jt}, \phi^{jt}(D^{jt}, K^{jt}, Y^{jt}, N^{jt})\right) \tag{1}$$

The distributions of D^{jt}, K^{jt}, Y^{jt}, and N^{jt} are affected by prior transportation prices and attributes as well as other factors not related to transportation policy, X^{jt}. So ϕ^{jt} can be written as a function of prior transportation prices and attributes and nontransportation factors:

$$\phi^{jt} = \Phi\left(p_{\mathrm{o}}^{j,t-i}, p_{\mathrm{a}}^{j,t-i}, A_{\mathrm{o}}^{j,t-i}, A_{\mathrm{a}}^{j,t-i}; X^{jt}\right) \qquad i = 1, 2, \ldots, \infty. \tag{2}$$

Substituting Eq. (2) into Eq. (1) we have ridership as a function of current and lagged transportation prices and attributes, plus a set of nontransportation realted factors:

$$R^{jt} = h\left(p_{\mathrm{o}}^{j,t-i}, p_{\mathrm{a}}^{j,t-i}, A_{\mathrm{o}}^{j,t-1}, A_{\mathrm{a}}^{j,t-1}, X^{jt}\right) \qquad i = 0, 1, \ldots, \infty. \tag{3}$$

Supply

We are not interested in a full exploration of a transit authority's objectives and associated supply functions; rather, we need only identify factors affecting the authority's pricing and service levels that are independent of current demand conditions. Government subsidies and changes in the authority's cost structures over time are good candidates. For simplicity, we assume that a transit authority with a single-year planning horizon chooses price and service level at each station to maximize its ridership, given exogenously determined costs and governmental operating subsidies S^t: Costs are assumed to be linear in A_{o}^{jt}, with a per unit cost of C^t so the transit authority's maximization problem is

$$\begin{aligned} &\text{Max} \quad R^{jt} \\ &\text{ST} \quad \sum_{j=1}^{t} p^{jt} R^{jt} + S^t = C^t \sum_{j=1}^{J} A_{\mathrm{o}}^{jt}. \end{aligned} \tag{4}$$

A revenue-maximizing authority would set its price and service levels based on market forces reflected in ridership and exogenous factors affecting subsidy levels and cost structure.

$$\begin{aligned} p^{jt} &= f(R^{jt}, S^t, C^t) \\ A_{\mathrm{o}}^{jt} &= g(R^{jt}, S^t, C^t) \end{aligned} \tag{5}$$

[8] See Voith [13] for a complete discussion of the model.

Of course, ridership is a function of current and lagged price and service levels as shown in Eq. (3).

III. EMPIRICAL SPECIFICATION AND ESTIMATION

We investigate two alternative empirical specifications of Eq. (3), both of which employ a geometric lag that is the same across variables and stations.[9] The first specification is a fixed-effects model shown below:

$$R^{jt} = \beta_1 \sum_{k=0}^{\infty} \lambda^k p_{\mathrm{o}}^{j,t-k} + \beta_2 \sum_{k=0}^{\infty} \lambda^k p_{\mathrm{a}}^{j,t-k} + \beta_3 \sum_{k=0}^{\infty} \lambda^k A_{\mathrm{o}}^{j,t-k} + \beta_4 \sum_{k=0}^{\infty} \lambda^k A_{\mathrm{a}}^{j,t-k} + \delta^j + e^{jt}. \tag{6}$$

The fixed-effects model looks only at deviations from within-group means for each station. This formulation has the advantage that differences in ridership across stations that are the result of unobserved factors correlated with, but not caused by, service characteristics do not bias the estimates of the coefficients of interest. The fixed effects essentially correspond to the effects of the subset of X^{jt} variables that do not vary over time.[10] The estimated fixed effects, δ^j, are of interest because they are the differences in ridership across stations not explained by price and service changes over the sample period.

The second specification is a transformation of Eq. (6) into first differences. The first difference specification may be desirable because the price variables are likely to be nonstationary in levels but not in first differences. The fixed effects terms, δ^j, drop out of the first difference specification. Still, if there were differential growth rates across stations that are unexplained by changes in prices and service, we could find significant fixed effects in this specification. We test for this possibility.

Ignoring for a moment the issue of simultaneity in ridership, price, and service levels, Eq. (6) can be estimated directly using a nonlinear regression on observable lags and an unobservable component that is a function

[9] There are two concerns in the specification of Eq. (5). One issue is whether the lag structure is the same across price and service variables. Another issue is whether parameters are the same across stations. For example, do short train trips have the same price elasticity as long trips? SEPTA's behavior with regard to its pricing and service changes over time is consistent with the notion that SEPTA managers believe that elasticities may differ spatially.

[10] As discussed earlier, we have included a number of time-varying variables aside from price and service levels, including city employment, dummy variables for strikes, disruptions, etc., in addition to the fixed effects.

of the geometric lag parameter and initial conditions.[11] Denoting the price and service variables and their associated parameters by Z^{jt} and γ, respectively, Eq. (6) can be written as

$$R^{jt} = \gamma \sum_{k=0}^{T-1} \lambda^k Z^{j,t-k} + \gamma \sum_{k=T}^{\infty} \lambda^k Z^{j,t-k} + \delta^j + e^{jt}. \tag{7}$$

In this equation, the first term is observable, with each observation including all available lags of the price and service parameters. Depending on t, the number of lags available for each observation varies. For example, for $t = 12$, there will be 11 lags included; for $t = 2$ there is only 1 lag. The second term includes presample lags and hence is unobservable, but can be shown to be a function of the geometric lag parameter and initial conditions. The effects of the unobserved, presample lags are captured in a "truncation remainder" which can be written as

$$\lambda^{T-1} b^j = \lambda^{T-1} \sum_{k=T-1}^{\infty} \lambda^k \gamma Z^{jt-k}.$$

Thus the second term in Eq. (7) can be rewritten as $\lambda^{T-1} b^j$, where b^j is a function of unobserved initial conditions at each station.[12] The b^j parameters cannot be estimated consistently although all other parameters can be. Including the term in the estimation controls for the effects of initial values on the current levels of ridership. The reported estimations for both the ridership level and first difference estimations are based on this specification.[13]

A serious concern is simultaneity in ridership, price, and service levels. As argued in Voith [13], institutional factors tend to mitigate against simultaneous determination of ridership, fares, and service levels. Timing of fare increases depends on the pace of the public hearing process, and service frequency and speed are predetermined by half-yearly schedule changes. Moreover, the need for fare and service changes is likely to

[11] See Hsiao [6] for the details of estimating a geometric lag using panel data. Voith [13] provides an empirical example.

[12] In the first difference specification, initial conditions are assumed to be the same across stations. That is, we assume that the initial first differences are not systematically different across stations.

[13] An alternative approach to estimation follows from the fact that (6) can be transformed into a linear dynamic model of the form $R^{jt} = \lambda R^{jt-1} + \beta X^{jt} + \delta^j + \xi^{it}$. As noted by Sevestre and Trognon [10], if R^{j0} and δ^j are correlated, OLS estimates are inconsistent unless t becomes large. As usual, OLS is inconsistent if ξ is serially correlated. These problems can be overcome by estimating a first difference equation and using instrumental variables (using current and lagged values of price and service variables as instruments) for $R^{i,t-1}$. Results using this estimation procedure are qualitatively similar to those reported here.

depend largely on exogenously determined subsidies. Still, if transit managers correctly forecast changes in ridership and adjust fares and service levels accordingly, simultaneity could be a problem. To address the issue of simultaneity, we estimate Eq. (7) jointly with linear estimations of the price and service equations shown in Eq. 2 using nonlinear two-state least squares.[14] We use information on subsidies, costs, lagged deficits, and zone and line (interacted with SEPTA vs Conrail control) as instruments in the price and service equations. See the Appendix for the full specification.

IV. ESTIMATION RESULTS

We present estimations of the fixed-effects ridership level model and the first difference model for two samples. The first sample corresponds to the period estimated in Voith [13].[15] The second sample covers the entire period from 1978 to 1991. Both models include peak and off-peak number of trains, real round-trip fare, real variable cost of a round trip by car, and speed of the train. In addition, each estimation includes dummy variables for the years 1984, 1985, and 1986, which are the years following a 3-month system-wide shutdown due to a strike in 1983. Qualitative variables for service reliability, service interruption, changes in transit competition, and changes in auto competition are also included.[16] These variables are included to control for changes in the relative attractiveness of the train that are not reflected in the other variables. They are scaled such that the expected sign, which is generally obtained, is positive. Finally, we include employment in the city of Philadelphia to capture changes in the size of the destination market.

Fixed-Effects Ridership Level Model

Estimates of the fixed-effects ridership level model, shown in Table 4, reveal broad similarities across the sample periods. The coefficient estimate of the lag parameter and peak service levels are somewhat higher in

[14] The model is linear in the endogenous variables so we do not need to augment the instrument set with squares or cross products of the exogenous variables as is often the case in nonlinear two-stage least squares.

[15] While the coefficient estimates are qualitatively similar to those published in Voith [13], neither the model nor the sample is exactly comparable. The model shown in Table 4 includes additional variables that reflect qualitative factors affecting ridership at any station at a particular point in time. In addition, Philadelphia employment is not included in the earlier estimations. The sample differs in two respects. Although the sample covers the same period, the observations are roughly annual, rather than 12 observations over 8 years as in Voith [13]. Also, because of data limitations, there are eleven fewer stations in the current analysis.

[16] None of the dummy or qualitative service variables are entered with lags. For the first difference regressions, the qualitative dummy variables are transformed into changes from year to year.

TABLE 4
Fixed-Effects Estimation Results

	1978–1986 OLS		1978–1991 OLS		1978–1991 2SLS	
	Coef	SE	Coef	SE	Coef	SE
Number of peak trains	5.60*	2.42	7.71*	1.64	9.20*	2.56
Number of off-peak trains	5.15*	0.85	3.19*	0.51	3.25*	0.72
Speed	3.12*	1.34	1.66*	0.78	1.69**	0.98
Round-trip fare	−37.15*	5.84	−25.60*	3.00	−32.05*	4.08
Variable cost, auto	4.69	8.49	3.16	3.26	2.41	3.94
Employment	−1.11*	0.49	0.22	0.15	0.15	0.16
Dummy, 1984	−98.48*	10.33	−78.63*	8.78	−81.36*	9.75
Dummy, 1985	−33.33*	8.71	−27.06*	7.79	−28.83*	8.48
Dummy, 1986	37.84*	12.06	30.95*	8.05	34.36*	8.94
Dummy, reliability	−23.77	23.76	14.22	12.28	16.14	13.61
Dummy, interruptions	13.70	20.07	52.59*	11.07	48.63*	14.07
Dummy, transit	72.09*	12.74	68.20*	10.88	71.38*	14.44
Dummy, highway	40.78*	11.54	49.58*	7.70	41.71*	9.09
λ	0.44*	0.04	0.52*	0.03	0.42*	0.04
Number of observations	944		1534		1534	

Note. Dependent variable: Ridership.
* Significant at the 95% level.
** Significant at the 90% level.

the full sample, while the impacts of price, off-peak service level and speed are a little lower.[17] Two-stage least-squares (2SLS) estimates of the model for the whole sample, shown in column 3, are very similar to the OLS estimates, although the coefficient on the lag parameter is about 20% lower. Based on the 2SLS estimates for the whole sample, the lag parameter, at 0.42, implies a long-run effect that is roughly 1.72 times as large as the initial impact and has a mean lag of almost 9 months.[18] The estimated lags are considerably shorter than those reported in Voith [13], which implied a long-run effect of about 2.6 times the short-run effect.

[17] With regard to the other factors that affect ridership (which are assumed to affect ridership only contemporaneously), the strike of 1983 had a large negative impact in 1984 and 1985, as reflected in the coefficients on the dummy variables for these years. The dummy variables for service interruptions, transit competition, and highway competition generally are significantly positive as expected. The dummy variable for reliability is always insignificant. Finally, employment in Philadelphia has a positive but insignificant effect on ridership. The commuter rail system effectively serves only CBD workers, and employment in the CBD, which is service oriented, may not always move in the same direction as overall city employment.

[18] The long-run effect is $\beta/(1-\lambda)$, where β is the estimated coefficient and λ is the estimated lag parameter. The mean lag, or length of time it takes for half of the lagged effect to occur, is $\lambda/(1-\lambda)$.

The magnitudes of the estimated service coefficients are economically significant. Consider the effects of service frequency. Based on the 2SLS whole sample estimates, adding an additional peak train increases ridership at a particular station by 9.2 passengers in the short run and by 15.4 passengers in the long run.[19] While adding a train would reduce a station's average passengers per peak train (about 28 riders per peak train), the long-run increase is more than double the average number of passengers boarding an off-peak train (5.3). An additional off-peak train results in an increase of 3.3 passengers in the short run and 5.6 in the long run. Thus, adding an off-peak train lowers average ridership per off-peak train in the short run, but in the long run, average ridership per off-peak train is unchanged. Given the considerable fixed costs associated with providing commuter rail service, increasing service levels almost certainly results in lower subsidies per passenger.

As is the case with service frequency, speed is positively related to ridership. At 1.69, the coefficient on speed implies that increasing speed from the average of 24 miles per hour to 30 miles per hour would increase ridership by 5.3% in the long run.

With regard to real fares, the estimates imply greater elasticities than the -0.3 commonly cited in the literature.[20] Based on the 2SLS whole sample estimates, the coefficient of -32.1 implies a short-run own price elasticity of -0.59 when evaluated at the sample average ridership and price. The long run elasticity is -1.02. The short-run elasticity is similar to that reported in Voith [13]. If ridership is indeed price inelastic in the short run but unit elastic in the long run, transit authorities with single-year planning horizons may choose pricing strategies that are not revenue maximizing in the long run.

The coefficients on the variable cost of auto commutes are insignificant in both samples and in both OLS and 2SLS estimations. The fact that this variable is insignificant is not surprising, however, as changes in the variable are driven by factors—per-mile operating costs and parking fees—that have no cross-sectional variation and may be correlated with other region-wide factors.

First Difference Model

Because the price variable has an upward trend component (see Fig. 1) estimates of its impact on ridership using levels may be unreliable. To address this issue, we reestimate the model for both samples using first

[19] The coefficient on peak number of trains yields the effect on total ridership, not just peak ridership. Peak ridership is roughly 68% of the system total. The calculations of effects per train are based on sample-wide average peak and off-peak ridership and number of peak and off-peak trains.

[20] See Small [11].

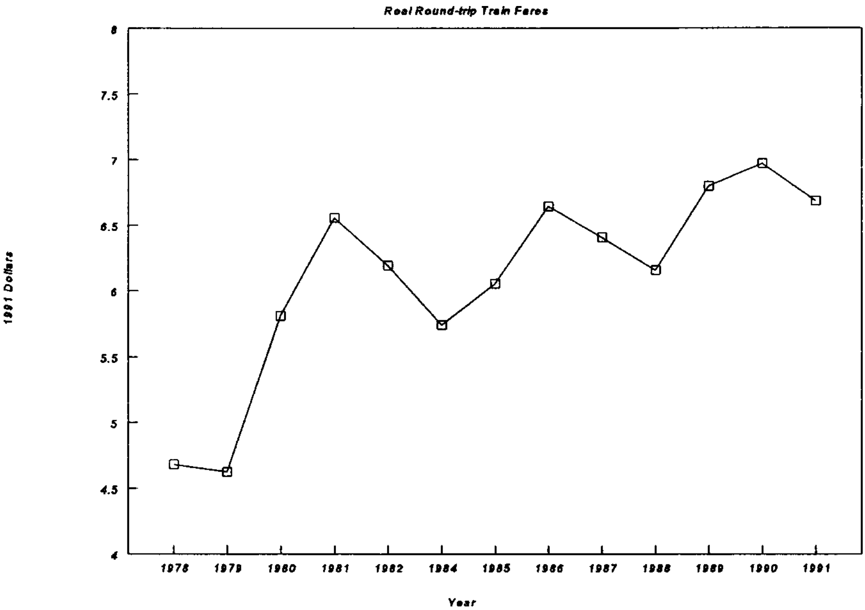

FIGURE 1

differences rather than levels. The first difference model differs from the levels model in that there are no station-specific fixed effects. An F test indicates that the hypothesis of no significant differences in growth rates across stations cannot be rejected.

Estimates of the short-run impacts of service levels and speed from the first difference model are generally smaller than those of the fixed-effects model while price effects are nearly the same. Generally, the estimates are consistent across samples, although the estimate of peak service effect is small and insignificant in the shorter sample and the estimated lag parameter is considerably larger than that from the full sample. The 2SLS estimation implies smaller impacts for service frequency but slightly larger price impacts than the OLS estimation. Unlike the case of the fixed-effects model, 2SLS first difference estimations result in a higher estimate of the geometric lag parameter. The results of the first difference estimations are shown in Table 5. We focus on the 2SLS results from the full sample.

The estimated lag parameter is 0.52, implying a mean lag of a little over a year and long-run effects that are twice as large as short-run effects. The point estimate of the impact of peak service frequency, at 3.0, is insignificant, only about one-third the magnitude of the fixed-effects estimate. The estimated long-run impact remains statistically significant. Adding an

TABLE 5
First Differences Estimation Results

	1978–1986 OLS		1978–1991 OLS		1978–1991 2SLS	
	Coef	SE	Coef	SE	Coef	SE
Number of peak trains	1.03	2.74	3.75	2.45	3.03	4.39
Number of off-peak trains	4.76*	1.00	4.18*	0.84	2.38**	1.24
Speed	2.73	1.70	1.32	1.59	1.14	1.58
Round-trip fare	−26.66*	7.31	−26.69*	4.43	−30.24*	5.19
Variable cost, auto	−18.64**	10.23	−4.03	4.94	−1.55	5.21
Employment	0.16	0.94	0.16	0.23	0.20	0.24
Dummy, 1984	−103.15*	14.49	−100.33*	8.34	−99.59*	8.42
Dummy, 1985	−42.27**	24.21	−41.59*	8.77	−41.82*	8.82
Dummy, 1986	17.50	34.60	24.38*	7.37	25.80*	7.43
Dummy, reliability	−5.98	17.50	−6.84	10.59	−3.64	10.67
Dummy, interruptions	−2.44	18.52	21.53**	11.11	20.20**	11.16
Dummy, transit	63.32*	16.30	56.31*	13.75	56.76*	13.98
Dummy, highway	27.05*	13.35	24.43*	9.40	25.84*	9.38
	0.64*	0.10	0.49*	0.09	0.52*	0.09
Number of observations	826		1416		1416	

Note. Dependent variable: Ridership.
* Significant at the 95% level.
** Significant at the 90% level.

additional peak train will generate 6.3 riders at a given station in the long-run, less than half of the 15.4 estimated from the fixed-effects model. Adding an off-peak train results in a statistically significant short-run increase of 2.4 passengers and a long-run increase of 5.2 passengers. Unlike the estimate based on the fixed-effects model, adding an off-peak train does not maintain the average number of riders per train in the long run; rather it falls slightly. With respect to speed, the point estimates are about half the size of the fixed-effects regression and insignificant.

At 30.2, the coefficient on the fare variable is highly significant and of roughly the same magnitude as the estimate from the fixed-effects equation. It implies a short-run elasticity of −0.56, which is still considerably above the commonly accepted −0.3. The larger long-run multiplier implies that ridership is slightly elastic (−1.14) in the long run. The coefficients on the variable cost of auto travel are of the wrong sign, but small and highly insignificant.

OLS versus 2SLS Estimates

The biggest difference between the OLS and 2SLS estimates is in the magnitude of the lag parameter but the direction of change from OLS to 2SLS differs in the fixed effects and first difference models. There are other differences between the OLS and 2SLS estimations, but qualitatively, the results are very similar. On the surface, the similarity between the OLS and 2SLS estimations is somewhat surprising. It seems likely that service levels should be adjusted in response to demand for service. Prices should adjust as well, although perhaps not as quickly, given institutional constraints on changing fares. In facts, SEPTA management has stated its unwillingness to raise fares during periods in which they perceive weak (but statistically unexplained) demand and have attempted to intertemporally shift resources to avoid fare increases.

Despite these considerations, there are two reasons why price and service at the station level may be less endogenous to ridership than we would otherwise expect. First, adding a train to a particular line increases service levels to all or most stations on the line, so that even stations with weak demand enjoy service increases.[21] Second, the link between station level ridership and fares is reduced because SEPTA fares tend to be changed systematically for distance-based groups of stations.[22] This practice results in all stations in a given group facing the same fares, whether demand is weak or strong.

V. ANALYSIS OF RESIDUALS: RIDERSHIP AND RIDERSHIP CHANGES ACROSS STATIONS

The estimations above attempt to explain commuter rail ridership and ridership change as a function of transportation prices and service attributes. Other factors affecting commuter rail demand at the station level are impounded in the estimated fixed effects, which are best understood as the station-specific component to ridership level that is not explained by the within-station variation in the independent variables. In terms of the analytical framework, these fixed effects correspond to the nontransportation related variables, X^j.[23] In the following subsections we evaluate the role of demographic factors in explaining cross-station fixed effects.

Unexplained Ridership Differences across Stations

The estimated fixed effects from the levels estimation vary from 12 to 1417 with a mean of 404 and a standard deviation of 264, suggesting considerable unexplained variation in the level of ridership across

[21] This is mitigated to the extent that limited stop train service is used.

[22] After 1982, all SEPTA stations within a given distance-based zone received identical fare changes.

[23] Because our measured demographic variables do not vary through time, we cannot include them directly in the estimating equation without dropping the fixed effects. Dropping the fixed-effects variables is likely to bias the estimates of the impacts of the price and service variables because of unobserved station factors affecting ridership across station.

TABLE 6
Estimations of Fixed Effects and Demographic Variables

	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Intercept	208.51	262.23	345.47	284.97	159.79	193.93	347.34	207.16
Mean household income/100	−0.02	0.24	−0.04	0.26	0.06	0.18	0.10	0.19
Percent of employees working in the CBD	6.88	7.28	10.80	7.83	3.66	5.39	5.61	5.72
Mean commuting time	−15.19	9.65	−10.75	9.85	−6.59	7.19	−3.44	7.20
Distance to CBD (miles)	7.31	5.39	1.15	10.11	3.24	4.01	−6.75	7.39
Vehicles per household	245.76**	136.50	154.23	152.08	54.57	102.87	−54.61	112.62
Population/100	0.50	0.35	0.54	0.35	0.49**	0.26	0.57*	0.26
Dummy, zone 1			−296.35*	147.20			−260.45*	107.07
Dummy, zone 2			−137.69	93.12			−78.49	67.97
Dummy, zone 4			14.40	93.17			62.15	67.90
Dummy, zone 5			66.24	169.70			228.39**	124.48
Parking spaces					1.54*	0.16	1.58*	0.16
Number of observations	116		116		116		116	
Adjusted R^2	0.17		0.17		0.55		0.56	

Note. Dependent variable: Fixed effects.
* Significant at the 95% level.
** Significant at the 90% level.

stations.[24] Factors that might affect ridership at a given station include the population near the station, the number of people living near the station that work in the CBD, average commute times of the location, the distance from the CBD, and income.[25] Using census tract level information (average of 1980 and 1990 values) and following the procedure described in Voith [14] to identify census tracts that have or are near commuter rail stations, we estimated several models relating the estimated fixed effects to the demographic variables. In these models, we also included one additional service variable—the number of parking spaces at the train stations—which could not be included directly in the ridership model because we had the data only for one point in time.

The results of these estimations are shown in Table 6. Four models were estimated; the first two do not include the parking variable and differ only in that the second includes dummy variables for fare zone. The remaining two estimations are identical to the first two except they include the parking variable.

The most striking aspect of these estimations is the lack of explanatory power of the demographic variables. In estimations without the parking

[24] The F test for the significance of the fixed effects is a highly significant 57.7.

[25] These variables may be endogenous to service quality and price, but we ignore that complication here.

variable, only the number of vehicles owned in the regression without the dummy variables for zone is significant (at the 10% level) and it has the wrong sign. None are significant in the estimation with the zone dummy variables. Additionally, there is little evidence of systematic spatial differences relating to fare zone. The adjusted R^2 in these regressions is only 0.16. In the estimations with the parking variable, the adjusting R^2 increases dramatically, but the only significant demographic variable is population. Fare zone also plays a slightly larger role. The bottom line is that demographic differences explain very little of the residual variation, once transportation is taken into account. It seems likely that the unexplained differences in ridership across stations result from unobserved differences in factors affecting the relative attractiveness of train service. History does seem to matter, however, as the residual fixed effects are highly correlated with current levels of service. The authority appears to adjust service levels in response to both observed and unobserved factors affecting demand.

Ridership Growth Differences across Stations

As is evident in Table 2B, there are considerable differences in ridership growth across stations. Despite this variation, there are no significant station-specific differences in ridership changes after controlling for price and service changes.[26] Given the lack of significant fixed effects on growth, it is not surprising that estimations of the ridership model that included 1980−1990 changes in the demographic variables listed above resulted in highly insignificant coefficients on the demographic variables. Thus, most of the variation in growth is a result of changes induced by changes in prices and levels of service. This is not to say that demographics play no role in ridership or ridership growth, but rather that demographic changes important to ridership are induced by transportation policy. To the extent that the demographic factors are functions of transportation policy, the effects of these factors are reflected in the estimates of the long-run impact of price and service and hence are not correlated with the estimated fixed effects.

VI. CONCLUSION

Using a panel data set on ridership, fares, and service levels, we have estimated a reduced-form fixed-effects model for ridership as well as a model (without fixed effects) for ridership changes. We find that the total

[26] An F test for the presence of fixed effects in the growth rate equations is a very insignificant 0.54.

impact of changes in fares and service levels occurs with a lag and that the long-run effects are roughly double the short-run effects. Ridership response to peak and off-peak service levels is statistically and economically significant, although the effects as measured from the first differences equation are somewhat smaller than those of the fixed-effects model.

The results with respect to price are generally consistent across samples and specifications. Both specifications yield short-run elasticities that are slightly larger than -0.5 and long-run elasticities that are unit elastic or slightly larger. The estimated elasticities are much larger than the commonly accepted -0.3 but substantially less than that reported in Voith [13].

Analysis of fixed effects from the ridership level model indicates significant variation across stations. Demographic variables, however, explain very little of the station-specific residual. After controlling for changes in prices and service attributes, we found no station-specific differences in ridership changes. Thus, the primary measurable determinants of ridership are related to transportation policy rather than to the ancillary effects of changing demographics.

APPENDIX

Estimates of the full system of equations for price, peak service, and off-peak service for the growth rate model are shown in Table A1. Note that the price equation includes dummy variables for zone, since all stations within a zone typically have the same price change. The zone dummies are interacted with SEPTA control (post-1983) because SEPTA appears to have pursued a different pricing strategy with respect to zone than did Conrail. Similarly for the service level equations, there are dummy variables for line, since most stations on a given line received similar changes in level of service. Again the line dummies are interacted with SEPTA control. The results are as expected: Subsidy increases lowered prices and raised service levels while cost increases raised prices and lowered service levels. Ridership increases significantly raised service levels. Because transit authorities can shift resources intertemporally, we also included the lagged deficit as a measure of tightness of the current budget. As expected, lagged deficits were positively related to price, but contrary to expectation, they were also associated with increased current service levels. Generally, the zone and line dummies tend to be more significant during the period of SEPTA control. The R^2 values of these models indicate that only a relatively small fraction of the variation of price and service levels is explained by the included variables.

TABLE A1

Price and Service Estimations: First Differences, 1978–1991 Sample 2SLS

	Price		Peak		Off-peak	
	Coef	SE	Coef	SE	Coef	SE
Riders/100	0.08*	0.03	0.18*	0.06	1.70*	0.17
Subsidy/100	−0.00	0.16	1.65*	0.27	7.34*	0.80
Cost	246.95*	57.55	−182.49**	100.29	−1504.06*	292.78
Deficit/100	−0.38*	0.17	1.45*	0.30	4.65*	0.87
Zone 1	0.12	0.08				
Zone 2	0.38*	0.05				
Zone 3	0.29*	0.05				
Zone 4	0.40*	0.07				
Zone 1 SEPTA	0.02	0.10				
Zone 2 SEPTA	−0.29*	0.05				
Zone 3 SEPTA	−0.25*	0.06				
Zone 4 SEPTA	−0.42*	0.09				
Line 2			0.05	0.15	0.17	0.42
Line 3			−0.02	0.22	−0.18	0.65
Line 5			−0.43*	0.14	−1.69*	0.40
Line 6			−0.45*	0.16	−2.56*	0.47
Line 7			−0.40*	0.19	−1.52*	0.55
Line 8			−0.04	0.15	−1.55*	0.44
Line 9			0.02	0.29	−0.14	0.84
Line 10			−0.31*	0.12	−0.31	0.36
Line 11			−0.50*	0.17	−1.59*	0.49
Line 12			−0.02	0.13	−0.08	0.39
Line 13			−2.08*	0.25	−0.32	0.73
Line 2 SEPTA			−0.23	0.18	−0.45	0.52
Line 3 SEPTA			0.05	0.27	−0.43	0.79
Line 5 SEPTA			0.45*	0.16	2.59*	0.48
Line 6 SEPTA			0.26	0.19	2.08*	0.57
Line 7 SEPTA			0.11	0.23	1.24**	0.67
Line 8 SEPTA			−0.16	0.18	1.36*	0.54
Line 9 SEPTA			−0.32	0.35	−0.22	1.02
Line 10 SEPTA			0.27**	0.15	0.03	0.43
Line 11 SEPTA			0.56*	0.20	1.64*	0.59
Line 12 SEPTA			−0.26	0.16	0.73	0.48
Line 13 SEPTA			2.55*	0.30	0.67	0.89
Number of observations	1416		1416		1416	
Adjusted R^2	0.07		0.13		0.16	

* Significant at the 95% level.

** Significant at the 90% level.

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