Costing Individual Railroad Movements

by

Wesley W. Wilson* and John D. Bitzan**

Prepared for

Federal Railroad Administration
Department of Transportation

September 2003

* Wesley W. Wilson is a Professor of Economics at the University of Oregon and a Research Affiliate at the Upper Great Plains Transportation Institute, Department of Economics, University of Oregon, Eugene, Oregon 97403-1285. Tele: (541) 346-4690. Fax: (541) 346-1243. Email: wwilson@oregon.uoregon.edu

**John Bitzan is an Assistant Professor in the College of Business and an affiliate of the Upper Great Plains Transportation Institute, PO Box 5074, North Dakota State University, Fargo, ND 58105. Tele: (701) 231-8949. Email: John.Bitzan@ndsu.nodak.edu

Acknowledgments

The authors gratefully acknowledge financial support from the Federal Railroad Administration, and research assistance from the staff of the Upper Great Plains Transportation Institute and from Chris Clark and Andrew J. Stahl of the University of Oregon.

Disclaimer

Executive Summary

Since it's beginnings, railroad cost analysis has developed along two separate and distinct paths. Academic economists have analyzed aggregate cost functions to examine issues such as economies of scale, scope, and cost subbadditivity. At the same time, government regulators and railroads have used cost analysis in an attempt to measure variable costs associated with specific movements. The analysis of costs that aims to measure variable costs associated with specific rail movements is referred to as railroad costing. This report examines the history of railroad cost analysis, examines some of the criticisms of current railroad costing methodologies, and presents some alternative methods for analyzing the costs of individual railroad movements.

Railroads operate under a network technology and are subject to a host of regulatory rules, which have evolved over time. For regulatory purposes, there is and has been a continuing need for accurate costing of individual railroad movements. Partial deregulation of the railroad industry has accentuated the need for accurate costing of individual movements. Individual movement costs are used to estimate revenue-to-variable cost ratios used in market dominance proceedings and for individual shipper and railroad rate negotiation. However, the practice of railroad costing has been under continuing criticism. These criticisms have focused on inconsistencies between the current costing procedures and economic theory. At the same time, however, the "theoretically correct" models of costs advocated by academic economists do not account for the specificity needed for individual movement costing.

For more than 60 years, a combination of accounting and statistical procedures have been used to estimate the costs of specific railroad movements. The first costing system (Rail Form A) was introduced in the late 1930s. More recently, in an attempt to improve individual railroad costing, the Uniform Rail Costing System (URCS) was developed in the late 1970s. These procedures define a set of railroad activities used to produce outputs. Annual financial accounts are mapped into the activities and regressed on output and capacity measures to estimate the portion of such activity expenses that vary with output. The variable costs attributable to specific movements are then estimated by determining the amount of output associated with specific shipments and the corresponding activity expenses. The primary advantage of these procedures is that they give cost estimates which are finely tuned to specific movement characteristics. The disadvantage is that they may not be entirely consistent with economic theory. Later in this report, we describe this approach to rail costing and document the various criticisms in some detail.

Over this same time period, academic economists have estimated railroad cost functions to make assessments of railroad technology. These cost functions have been aggregate in nature, focusing on broad issues such as returns to scale and cost subadditivity. While firmly grounded in economic theory, these cost studies have aggregated railroad outputs, networks, and movement characteristics in a way that has not allowed their use in individual movement costing. To evaluate such models in context of railroad costing, we review this literature on the econometric studies of cost functions.

In this study, we try two new approaches to estimate the costs of specific railroad movements. First, we estimate a multi-product cost function similar to recent research by Bitzan (1999) with controls for unobserved heterogeneity. Unlike previous econometric studies of railroad costs, our multi-product cost function uses a hedonic specification for outputs. Hedonic specifications allow for outputs to be aggregated, but indexed for different shipment characteristics. The shipment characteristics and network and operating characteristics reflect some of the inputs to the URCS program. In comparing estimated costs for individual movements from our first specification to URCS costs, we find that translog estimated costs tend to be lower than URCS generated costs. We also find that there is considerable variation in costs across railroads and shipment types (way and through versus unit train), but little difference in costs for a given railroad and shipment type. We conclude that this approach likely gives good estimates of the level of costs for given railroads across shipment types, but does not provide good estimates of shipment costs for shipments with different characteristics. Specifically, it provides a good estimate of the average cost of an average unit train shipment for a given railroad, but does not provide a good estimate of the cost of a specific unit train shipment that differs much from the average.

Our second approach draws from the New Empirical Industrial Organization approach (NEIO) to estimate costs through a pricing relation. Our intuition is that difficulties in estimating individual shipment costs result from the source of the underlying data. Economic cost function studies and the Uniform Rail Costing System both rely on annual operating expenses and operating statistics, which are aggregations of a multiplicity of shipments. From these aggregate data, the analyst must, through assumption and econometric practice, effectively disaggregate the data. In contrast, the NEIO approach uses individual shipment data relating the prices to movement characteristics to estimate the costs of specific shipments. Specifically, the STB Waybill Sample is used. The difficulty with the data is that input usage and input prices are not observed. Essentially, our model specifies rate as a dependent variable founded on a condition for profit-maximization. Our research then seeks to estimate costs through observations on rates and variables that explain costs and markups. Given the parameter estimates, we can calculate marginal costs of a movement and, again, compare with URCS-generated costs. This approach yields estimates of marginal costs that track URCS costs reasonably well over time . The estimates are slightly higher than URCS generated costs, but seem to be highly correlated. In our research, the correlations between URCS and NEIO-costs run between .68 and .78. While this research is the first of its kind and most assuredly needs further refinement, we think it has significant promise in the area of railroad costing.

TABLE OF CONTENTS

LIST OF TABLES

1. INTRODUCTION

Railroads have been federally regulated for more than 100 years. Regulation places constraints on the rates railroads can charge, the lines over which they operate, on merger activity and a wide array of other activities. A mandate of regulation is that railroads are not allowed to charge "unreasonable" rates. Implementation of this mandate, however, is complicated due to the nature of railroad markets, technology, and information requirements. Specifically, railroads produce outputs over a network. A railroad market is a flow of a commodity from one location to another. Since railroads haul large numbers of commodities between many locations and generally provide the services under conditions of joint production and economies of density, estimating the cost of a specific movement is no simple undertaking.

Over the history of railroad regulation, rail costing (i.e., the costing of a specific movement) has evolved for regulatory and bargaining purposes. That is, information gleaned from annual accounting records is used to develop approximations to the costs of specific movements. Such approaches include Rail Form A (RFA) developed in the 1930s and introduced to the regulatory environment in 1943, and the Uniform Rail Costing System (URCS)[1] developed in the late 1970s and early 1980s and adopted in the late 1980s.[2] As discussed later, these two accounting procedures differ in detail, but both use annual accounting figures to derive estimates of specific movement costs.

Coinciding with the development of RFA and URCS has been the development of an academic literature that uses econometric procedures to estimate costs. This literature aims at uncovering the structure of costs and, in particular, whether there are economies of scale, density, and scope in railroad production. This approach has also been used to examine the influence of technological progress, effects of partial deregulation, and effects of specific operating and network characteristics of firm production. The specifications used to estimate costs follow directly from economic theory. Firms minimize costs given the level of output(s), factor prices (e.g., labor, fuel, etc.), fixed factors, and a set of variables that index technology. Generally, these are titled operating and/or network characteristics. Measures of each class of variables are largely derived from the same reports used in RFA and/or URCS. However, unlike RFA and URCS, the academic cost studies place little structure on the technology of the firm. Specifically, in recent years, "flexible" functional forms, especially the translog, have been used to estimate cost functions. In its most general form, costs are not necessarily constant (i.e., there may be economies of scale and economies of density), inputs may be substitutable or complementary to one another, etc. In this literature, however, only scant attention is paid to the costing of specific movements[3] and, as already noted, the primary data represent aggregations of network activities. In Section 3, we develop and estimate a relatively general model of railroad costs and apply it to

---

[1] The impetus for URCS is found in the Railroad Revitalization and Regulatory Reform Act of 1976, which mandated the Interstate Commerce Commission to develop a costing system that was more comprehensive than RFA. This mandate resulted in a change in the accounting data required of railroads (the Uniform System of Accounts was replaced) and the development of URCS.

[2] See Bereskin (1989), McBride (1983), and Westbrook (1988) for discussion and historical development.

[3] Bereskin (mimeo) provides the only in depth analysis of using econometrically estimated cost functions to estimate the costs of a specific movement.

the available “system” data following conventions of the literature. We then calculate incremental costs of movements and compare our estimates with URCS-generated costs for the same movements.

An alternative approach presented in this report uses disaggregate data to estimate costs of a movement. The approach is based on the *New Empirical Industrial Organization* (NEIO) approach. The NEIO model is an econometric model of an industry (Bresnahan (1989)). In a fully specified form, it consists of a model of demand, costs, and pricing. In the model, prices, output, and costs are determined by equilibrium conditions. In the context of railroad costing, we follow a classic paper published in *Econometrica* by James Rosse (1970). In this frame of reference, cost function parameters can be estimated through a pricing relation and a specification of the determinants of costs. More specifically, the marginal condition for profit maximization is used to frame a model of prices. Prices are explained as a function of cost determinants, (e.g., factor prices and output), and as a function of demand and competitive conditions. As applied to railroad costing, rates attached to specific movements, factors affecting costs, and competitiveness variables are readily available in the waybill sample. We employ this methodology in Section 4 to infer marginal costs from a model of prices and markups.

In the following section of the paper, we provide a summary of RFA and URCS with more detailed descriptions of the econometric and NEIO literatures. In Section 3, we present our general railroad cost model, while in Section 4, we describe results using the NEIO framework. Section 5 provides a summary of our findings, caveats, and suggestions for future research.

2. BACKGROUND

In this section, we provide a brief history and description of railroad costing.[4] To the interested reader, we also provide a relatively detailed description of literatures that correspond to our analyses in Section 3 and 4. For brevity, these are provided in Appendices A and B. In Appendix A, we provide a description of the literature which examines econometric analysis of costs and the associated applications to railroads.[5] In Appendix B, we describe a general framework titled the NEIO, with a discussion of related research in railroad economics that follow this general modeling framework.

2.1 History and Evolution of Railroad Cost Analysis

There is a long history of railroad cost analysis. Some of the earliest contributions to the statistical analysis of railroad costs are attributed to M.O. Lorenz (1916) and J.M. Clark (1923).[6] However, since its beginnings, railroad cost analysis has developed along two separate and distinct paths. As mentioned previously, academic economists have analyzed aggregate cost functions to examine issues such as economies of scale, scope, and cost subadditivity. At the same time, government regulators and the railroads have used railroad cost analysis in an attempt to measure variable costs associated with specific rail movements. The analysis of costs that aims to measure variable costs associated with specific rail movements is referred to as railroad costing. This section of the report discusses some of the history of railroad costing and the general approach used, provides a detailed description of the state-of-the-art in railroad costing (the Uniform Railroad Costing System), and discusses some of the problems associated with railroad costing.

Railroads, like any other business, have always had a need for detailed cost information to set rates, to examine the profitability of various operations, and to make investment decisions. Moreover, the need for detailed cost information has been even greater in the rail industry due to a history of economic regulation.[7] With regulation came a need for movement-specific cost information by regulators, who used this information to examine the reasonableness of rates and the financial viability of the industry, and in enforcing the common carrier obligation to serve specific rail routes. Several authors have attributed bankruptcies of the 1970s, lack of innovation, and traffic misallocation to this era of regulation.[8] Nearly 100 years later, partial deregulation via the 4-R and the Staggers Acts gave much more freedom to the market in establishing market outcomes.

---

[4] For more complete descriptions of URCS see ICC (1982) and RAPB (1987). For critical reviews and discussions, see Westbrook (1988), McBride (1983), Waters and Woodland (1984), and a litany of other described later.

[5] The literature in this area is vast and our discussion is cursory by intention.

[6] Waters and Woodland (1984).

[7] Federal regulation of railroads began with the Interstate Commerce Act of 1887.

[8] See the classic books by Meyer, Peck, Stenason, and Zwick (1959); and Friedlaender and Spady (1981) with more recent research by Barnekov and Kliet (1990); Boyer (1977; 1981); Burton (1993); MacDonald (1987, 1980); MacDonald and Cavallusso (1996); McFarland (1989); Wilson (1994, 1996a); Winston (1985; 1993); and Winston et al. (1990) and a litany of others underscoring the effects of regulation and savings of partial deregulation. Winston (1993), in particular, provides a concise synopsis of the distortions created by regulation.

This freedom allowed railroads more choices in pricing their individual services (Tolliver, 1984, p. 4), bringing with it the introduction and adaptation of new services (e.g., contract rates, COTS programs, etc.), and tremendously reducing the level of inefficiency in the industry.[9] The result of partial deregulation is that rates and costs of service have fallen across wide ranges of traffic classifications.

This partially deregulated market, however, has led to an even greater need for measuring railroad costs. Rail rates and the "fairness" of those rates, as practiced by the Interstate Commerce Commission, are more subjective in nature and much harder to assess.[10] Less reliance can be placed on published rail rates, since rates are increasingly formulated through individual contracts (McBride, 1983, p. 45).

In response to growing pressure for better measurement of railroad costs, the Interstate Commerce Commission (ICC) mandated the development of the Uniform Railroad Costing System, better known as URCS, (Bereskin, 1989, p. 102) in the mid-1970s. The development of URCS was an attempt at addressing some of the short-comings of the previous costing system, Rail Form A (RFA), while retaining the accounting-based methods.

2.2 A Summary of RFA and URCS

The ICC has used either RFA or URCS to estimate railroad costs associated with specific shipments since 1938. Although RFA and URCS have some differences, they use the same general approach in estimating variable costs associated with specific rail movements. The general approach is described here.

RFA and URCS use an activity approach to estimate the variable costs associated with specific shipments. That is, rather than estimating a cost function, RFA and URCS attempt to explain costs of performing various railroad activities such as track maintenance, freight car repairs, and road train inspection. The costs of performing these activities are statistically related to capacity measures (e.g. track miles) and output measures (e.g. train miles) through linear regression. The portion of these expenses explained by output measures are hypothesized to be variable, while the portion explained by capacity are deemed to be fixed. Once the portion of various expenses hypothesized to be variable is obtained, the variable costs of specific movements are estimated by determining the amount of output associated with specific shipments (e.g. train miles) and their corresponding impacts on various activity expenses.

Although the URCS is set up in a similar manner to RFA and is designed to answer the same questions, there still are some differences. Specific differences include: (1) differences in the underlying accounting data used to estimate activity expenses, (2) differences in the way variability percentages for activities are treated, (3) differences in explanatory variables used, and (4) differences in the accessibility of movement-specific costs to individuals. Each of these differences are discussed, in turn.

---

[9] See Wilson (1994; 1996; 1997); Bitzan (1999); Bitzan and Keeler (forthcoming); Burton (1993); Barnekov and Kliet (1990); MacDonald (1990); and MacDonald and Cavallusso (1996); and Corsi, Winston, and Evans (1990) and others for discussion.

[10] See Wilson (1996) for discussion of market dominance in terms of regulatory practice and in terms of a theoretical model of railroad limit pricing.

One major difference between URCS and RFA is in the underlying accounting data used. Coinciding with the development of URCS was an effort to revise the accounting system used for Class I railroad reporting (ICC, 1982). Specifically, expense accounts are more precisely defined by breaking them into smaller components and by eliminating "catch all" components. Moreover, accounts are broken into four components of salaries and wages, materials and supplies, purchased services, and general expenses (ibid). Finally, multi-year period expense data are averaged prior to their use in URCS to prevent variations from year to year that are the result of maintenance cycles. It is argued that data refinements for the application of URCS improve the accuracy of movement-specific costing in URCS in comparison to that performed with RFA (ibid).

Another major difference between URCS and RFA is in their treatment of variability percentages. For each activity account, URCS estimates a different variability percentage for each carrier based on that carrier's level of activity (ICC, 1982). On the other hand, RFA estimated one variability percentage for each account. This variability percentage was applied to all carriers. Moreover, URCS estimates a different variability percentage for each carrier every year, while RFA estimated an industry-wide variability percentage infrequently (Ibid).

A third difference between URCS and RFA is in the statistical formulations used. URCS uses an expanded set of equations in comparison to RFA (ICC, 1982).

Finally, URCS incorporates the cost information into a computer program that can be used to estimate the variable costs associated with any specific rail movement. This computer program is accessible to the general public, making rail cost information more readily available to shippers and others interested in movement specific costs.

While the URCS attempts to address some of the failings of the RFA method, it is not without flaws. We now provide a brief overview of the URCS costing system and then examine some of the criticisms.

The Uniform Railroad Costing System is a "complex set of procedures, which transforms reported railroad expense and activity data into estimates of the costs of providing specific services." (ICC, 1982, p. 1-1) Mechanically, it consists of three computerized phases. In Phase I, regression equations are estimated for 15 individual cost accounts. Regressions are specified with the individual cost item as a function of output (e.g. gross ton-miles) and railroad capacity (e.g. road miles). In Phase II, individual railroad unit costs are estimated. Specifically, railroad capacity measures and output measures are plugged into the regression equations. The percent of each cost account that is variable expense is estimated. Then unit costs are estimated by multiplying the percent variable by that railroad's cost in a particular category. Finally, unit costs are added by output measures or service units (e.g. gross ton-miles). In Phase III, variable costs of specific movements are estimated through a multi-step process. First, the number of service units are computed, given the attributes of the shipment. Second, service units are multiplied by each unit cost to get the costs attributable to each activity for a particular shipment. Last, the total activity costs are added for an estimate of total variable costs (ICC, 1982). A more detailed description of the Phase I regressions follows.

Since inception, various authors have remarked on limitations of the URCS format. However, for demonstrative purposes, the upcoming formulaic expressions follow the notational development of Rhodes and Westbrook (1986). Let the variable cost function be represented by:

$$(1) \quad VC = R(q;1)C(q;1) + R(q;2)C(q;2) + \cdots\cdots + R(q;K)C(q;K),$$

where R is the variability ratio (weight) and C is the cost function for the k^{th} cost category, and q represents railroad output.

The cost function, designed to encompass total costs of the k^{th} category, is itself a function of variable costs (V) and fixed costs (F). Thus,

(2) $C(q; k) = F(k) + V(q; k)$.

In following, the variability ratio (R), symbolizes the portion of total costs in each cost category that are variable with relation to output. In notational form, this becomes

(3) $R(q; k) = [\ \{V(q; k)\}/\ \{F(k) + V(q; k)\}\ ]$

Given the above functional format, estimation procedures are used to establish R(k), the variability ratio. In this frame of reference, a linear cost function of the kth cost category takes the form:

(4) $C(k) = \alpha S + \Sigma\ \beta_m q_m$,

where S is a measure of fixed capacity and q_1, …., q_m are individual output measures. In this model, α and β are parameters to be estimated. Note that this specification is for only one of the activities and, as such, both the parameters and variables could be indexed by k. In this mode, αS can be interpreted as fixed costs associated with the kth category {F(k)}, while the sum $\{\Sigma\ \beta_m q_m\}$ represents variable costs {V(q; k)}. Using these estimates, the estimated variability ratio, R(k), now takes the form:

(5) $R(k) = (\Sigma\ \beta_m q_m)/\ (\Sigma\ \beta_m q_m + \alpha S)$.

With variability ratios for individual output measures being constructed:

(6) $R(k, m) = (\beta_m q_m)/\ (\Sigma\ \beta_m q_m + \alpha S)$

Therefore, the URCS process estimates R(k) and R(k, m) via cost equations such as:

(7) $C(k)_{it} = \alpha S_{it} + \Sigma\ \beta_m q_{mit} + \epsilon_{it}$,

where the railroad index is represented by i = 1,…, N and the time index by t = 1, …, T (Rhodes and Westbrook, 1986, pg. 291).

We use an example to illustrate the methodology. In equation (7), k indexes the kth expense category. In the URCS format, there exist 15 of these categories, delineated as follows:

- Running Track Maintenance
- Track Maintenance Overhead
- Running Crew Wages
- Transportation Overhead Expenses
- Transportation Fuel Expenses
- Road Locomotive Service and Repair and Overhead
- Road Train Inspection
- Clearing Wrecks
- Switching Maintenance and Overhead
- Yard Operations
- Switching Crew Wages
- Yard Locomotive Repairs
- Carload Related Expenses
- General and Administrative
- Freight Car Repair Overhead Expenses

The expense categories themselves are subjectively configured. They are based on railroad activities, with the grouping of costs based on "relatedness" (ICC, 1982, p. 3-3). For example, the expense category "Running Track Maintenance" consists of 10 related cost sub-categories, including Roadway, Bridges and Trestles, Ties, Rails, Other Track Materials, Ballast, Track Laying and Surfacing, Signals and Interlockers, Road Damage, and Grade Crossings. As such, these sub-categories all are assumed to fit into the more general category, "Running Track Maintenance." Likewise, the remaining 14 general expense categories are similarly configured (ICC, 1982, pgs. 3-6 and 3-11). These 15 accounts become the dependent variables in the generalized costing equation, represented by Equation 7.

Of the 75 major operating statistics collected from the railroads in the dataset, 13 form the explanatory variables. These 13 can be divided into two types: output variables and capacity variables (ICC, 1982, p. 3-12). The output variables consist of:

CLOR	Carloads Originated and Received
CM	Car-Miles, All Trains
GTM(C)	Gross Ton-Miles (Cars, Contents, Cabooses)
LRM	Locomotive Unit-Miles, Road Service
TH(S)	Train Hours, Total Switching
TH(W)	Train Hours, Way Switching
TH(Y)	Train Hours, Yard Switching
TM	Train Miles, Running.

Five variables represent capacity or size (ICC, 1982, pgs. 3-12, 3-16).[11] They include:

MR	Miles of Road, Total
ST	Miles of Track, Switching
T	Miles of Track Total
TR	Miles of Track, Running
Y(ST)	Miles of Track, Yard Switching

In the URCS, the 15 general expense (dependent) variables are estimated using capacity and output measures. However, as noted by the ICC (1982), as a general rule, one measure of capacity and one or more measures of output is instituted for each subsequent equation (p. 3-17). Again referring to Equation 7, the general capacity variable, S, is substituted for by the expense-specific capacity variables, listed above. The output variable, q, is similarly represented via the output variables, such as TM (Train-Miles, Switching). Thus, here it is assumed that capacity represents fixed costs, while the sought-after variable cost is estimated through use of the output variables.

Utilizing the previously mentioned explicit example of the expense category "Running Track Maintenance" (RMAINT), the regression takes the form of:

$$\text{RMAINT} = \beta_1 \text{TR} + \beta_2 \text{GTM(C)}$$

Likewise, the expense category "Transportation Fuel Expense" takes the form:

$$\text{RUNFUEL} = \beta_1 \text{TR} + \beta_2 \text{LRM}$$

As such, each of the remaining 13 equations are instituted similarly (ICC, 1982, pgs. 3-22 – 3-36). Table 2.1 (below) offers a complete listing of the 15 expense equation categories with their respective (accompanying) independent explanatory variables.

---

[11] The ICC text states there are 13 independent variables, but lists 14 in Table 3-4, p. 3-16.

TABLE 2.1. URCS REGRESSIONS

Expense Category	Output	Capacity
Running Track Maintenance	GTM(C)	TR
Track Maintenance Overhead	GTM(C)	TR
Running Crew Wages	TM	TR
Transportation Overhead Expenses	TM	TR
Transportation Fuel Expenses	LRM	TR
Road Locomotive Service & Repair & Overhead	LRM	TR
Road Train Inspection	TM	TR
Cleaning Wrecks	TM	TR
Switching Maintenance and Overhead	TH(S)	ST
Yard Operations	TH(Y)	Y(ST)
Switching Crew Wages	TH(Y)	Y(ST)
Yard Locomotive Repairs	TH(Y)	Y(ST)
Carload Related Expenses	CLOR	TR
General and Administrative	GTM(C)	TR
Freight Car Repair Overhead Expenses	CM(PD)	TR

2.3 Criticisms and Issues with URCS

As noted earlier, although the URCS is an attempted improvement over the previous RFA format, these procedures are not without fault. Most importantly, the “cost functions” as delineated by the URCS are not true cost equations. As commonly defined by economists, cost equations are established on theoretical grounds via “the nature of production” (Westbrook, 1988, p. 14). As such, a duality exists between cost and production functions (Bereskin, TRR, p. 13). This is not the case in the URCS framework. Here, methodology of establishing particular costs is an accounting-based procedure (Westbrook, 1988, p. 17). Thus, the “cost equations” used may be more accurately portrayed as “activity equations.”

A second issue is that the cost (activity) equations employed do not include an intercept term. Equations that omit the intercept term risk misspecification in that the slope, key to identifying incremental costs, must fit a line that goes through the origin. (Rhodes and Westbrook, 1986, p. 293).

The URCS also assumes strong separability and simple technological relationships in its framework (Bereskin, Mimeo, p. 3). For instance, each expenditure category is a composite of several related accounting measurements, accrued together. Each of these groupings of expenditures is then regressed on a single (multiple) output measure(s). Thus, the costs for each category are optimized on a stand-alone basis (separability). In defense of the simplistic technological approach taken, the URCS asserts that the railroad industry is mature and that "progressive changes in railroad technology…occur slowly over time" (ICC, 1982, p. 3-2). However, it should not be forgotten that there are strong theoretical suspicions to accruing "related" costs onto one measure of output, exclusive of all others. Moreover, there is strong empirical evidence in econometric cost studies of increasing returns to density.

Further, URCS total cost equations for each respective category (equation 7) also incorporate the dual assumptions that 1) expenditures on fixed inputs are proportional to capacity and 2) expenditures on variable inputs are proportional to output. Thus, as delineated, the total costs for a given category are simply a function of output and capacity (Westbrook, 1988, pgs. 18-19). This implies that costs and output vary proportionally, thus eliminating the inclusion of decreasing marginal costs (Rhodes and Westbrook, 1986, p. 291). Moreover, all inputs are assumed to enter the production function in fixed proportions, eliminating substitution among inputs to minimize costs (Rhodes and Westbrook, 1986, p. 291).

When considering the variability ratio, defined as the portion of variable costs to total costs for each expense category, the URCS maintains that the variability function is the same across all railroads. To do so, the URCS assumes that the variability function (R) only differs among railroads because of differences in input prices, ignoring that "variability functions may differ because of different input mixes" (Rhodes and Westbrook, 1986, p. 291). As such, the URCS maintains its hypothesis regarding identical variability functions through the assertion that "substantial uniformity of factor prices" exists among Class I railroads (ICC, 1982, p. 3-12). However, as noted by Rhodes and Westbrook, the optimal input mix is determined by production functions particular to each railroad, and by factor prices. Individual production functions are a product of individual railroad capacities, densities and scopes. This leads to the conclusion that the "optimal input mixes cannot be determined in the absence of relative factor prices, even if the prices *are* homogeneous across carriers" (Rhodes and Westbrook, 1986, p. 291).

The estimator chosen to estimate the given cost equations was Ordinary Least Squares (OLS), which has several benefits, namely the flexibility to incorporate any output and any cost-accounting category, such as in Equation 7 (Westbrook, 1988, p. 33). However, the use of OLS mandates several assumptions are needed to produce usable estimates. These assumptions appear to be violated. First, the URCS format uses OLS on panel data. This is tractable if the "econometric relationship is the same across railroads for every time period and if the econometric relationship is the same through time for every railroad" (Westbrook, 1988, p. 23). Moreover, since panel data are being used, this brings with it the dual suspicions of autocorrelation and heteroskedasticity. Although use of panel data (as compared to time-series or cross-sectional data) allows for richer, more pragmatic models, several authors have found that autocorrelation and heteroskedasticity are present in the dataset.[12] As such, the standard classical linear model expectations of a constant variance and uncorrelated error terms are assumed to be violated (Westbrook, 1988, p. 28).

---

[12] Authors include Westbrook (1988), and Rhodes and Westbrook (1986).

Additionally, the panel data involved is theorized by the URCS to be sampled from a "conceptually infinite superpopulation of all Class I railroads" (Westbrook, 1988, p. 22). This is not the case, however, for the sample actually is derived from a limited set of railroad firms. Furthermore, a portion of the variables in the panel data set (extending over a moving five-year period) are obtained from an ICC-based 1 percent Waybill Sample. The sampling characteristics of this representation also are unaccounted for in the URCS framework. Thus, a truly random sample is not achieved, but is assumed in the URCS (Rhodes and Westbrook, 1986, p. 292).

Another concern is that data underlying the URCS is subject to scrutiny. Historically, the ICC has mandated that the railroads provide certain expense and output measures for regulatory use (Bereskin, TRR, p. 16). As such, railroads have long submitted this information via the R-1 reports (RAPB, 1987, p. 99). Thus, the underlying URCS data procurement process has the benefit of longevity, being used for well over 50 years. However, in 1976 with the passing of the Railroad Revitalization and Regulatory Reform Act (4-R Act), the ICC "revised and expanded its prescribed regulatory system" (RAPB, 1987, p. 1). This led to the revision of the Uniform System of Accounts (USOC), the underlying data allocation procedure for the URCS. Although intended to update and improve, counterbalancing this is the knowledge that the data set fundamentally is inadequate for its intended use (Westbrook, 1988, p.16). As stated above, data reported by individual railroads is sufficiently aggregated that tying individual costs to a particular output is difficult. Further, provisions in the Staggers Act mandate that the data collection method "be obtained at the least possible expense and with the least possible information reporting," further ensuring data inadequacies (Westbrook, 1988, p. 15). Thus, the data set still is absent of many salient measurements in tracking costs, which would greatly aid the task at hand. Important examples include geographical and network effects, and measures for productivity trends (Westbrook, 1988, p. 15).

Given the discrepancies in the Uniform Railroad Costing System delineated above, it is not surprising that several authors have found fault. Daniel Westbrook notes that a "number of interested parties" have found the variability ratios to be "unreasonable" (Westbrook, 1988, p. 5). In addition, Westbrook, in conjunction with George F. Rhodes in a separate paper, finds the URCS "wholly inadequate" (Rhodes and Westbrook, 1986, p. 303). They cite the ad hoc methodology in specifying expense equations with the general, overall weak theoretical foundations instituted. This produces results that are econometrically unjustifiable (Rhodes and Westbrook, 1986, p. 303).

2.4 Synopsis

The theoretical and empirical weaknesses of the URCS should not be overstated. Many problems associated with the URCS merely are the result of difficulties associated with attempting to identify the costs of individual rail movements. As noted by several authors, railroads are multiproduct entities with output encompassing many dimensions including distance, time, geography, and weight (Bereskin, Transportation Research Record, p. 13). Moreover, these individual services often have joint expenses that are difficult to separate and attribute to particular outputs (Waters and Woodland, 1984, p. 4). Currently, URCS represents a practical and transparent attempt to estimate the costs of individual railroad movements. It strikes a compromise between theoretically correct aggregate cost functions and measurement of costs based on individual movement characteristics. In this report, we compare two other approaches. In Section 3, we present an econometric model of costs. In Section 4, we present an entirely different approach to the estimation of individual movement costs. This approach differs from both the URCS and the econometric cost function approaches in many ways. Most importantly, it has the basic unit of observation as a movement, not annual aggregations of movements.

3. ECONOMETRIC ANALYSIS OF COSTS

In this section, we describe our approach to estimating incremental costs using an econometric model of costs. As described in Appendix A, there has been a long history of econometric research pertaining to the econometric analysis of railroad costs. While our approach follows directly from this literature, we also present a theoretical model of railroad costs over a network in Appendix C. From this cost function, the costs of a specific shipment can be identified theoretically. However, the general version can not be implemented empirically given today's state of econometrics and data. The model is useful in identifying a theoretical ideal of railroad costing and some of the complications that arise in explaining the costs of individual movements.[13] In Section 3.2, we describe the model that we do estimate — a multiproduct model that follows the traditions of railroad economics. In Section 3.3, we document and describe the data employed, while in Section 3.4, the estimation results for the general model are presented. The goal of this chapter is to describe and apply the model for the costing of individual movements, and then to compare the results with the URCS method. This goal is accomplished in Section 3.5.

3.2 Econometric Modeling Approach

This section describes the econometric specification. Given the inadequacies of existing data and econometric methodology, we use aggregate measures of output. However, unlike the bulk of previous research in railroad economics, our specification is multiproduct and allows for heterogeneity in outputs. Specifically, we model costs using a hedonic translog cost function.[14] As noted by Spady and Friedlaender (1978) the hedonic approach rests on the definition of an "effective output". The effective output depends on a physical measure of output (e.g., a ton-mile) and also on a set of attributes (e.g., shipment size). That is, the hedonic output, $y = y\ (y, q)$, is a function that measures effective outputs in terms of a generic output (ton-miles) and a set of attributes associated with the generic output (shipment size). The underlying assumption of such a specification is that a continuum of different [attributes] measures of physical outputs exist, which can be consistently aggregated by the function $y_i(\square)$.

In our case, we use multiple hedonic functions. As discussed below, we define generic outputs for way and through operations and for unit train operations. We note that the delineation of outputs into multiple hedonic outputs allows factor utilization to vary across the hedonic outputs.[15]

---

[13] Due to length and mathematical principles of the model, it is placed in Appendix C.

[14] The hedonic translog cost function was first introduced by Spady and Friedlaender in 1978 for a single generic output. It was extended by to multiple generic outputs by Chaing and Friedlaender in 1985. Each of their applications pertained to the motor carrier industry. To our knowledge, this is the first hedonic model applied to railroad markets.

[15] Chaing and Friedlaender (1985) use hedonic functions for Less-Than-Truckload (LTL) and Truckload (TL) services. The factor mix used to produce LTL outputs quite likely is different than that of TL outputs. But, in the generic output, the factor utilization is the same. Similarly, the factor mix used to produce way and through outputs quite likely is different than that of unit train operations, but, in these classes, the factor mix is the same.

In our model, we use two hedonic outputs. In the data, we observe two types of activities through which railroads produce output over a network. These include unit train operations, which are "door-to-door" operations, and way and through operations, which follow a hub-and-spoke-type production process. That is, movements are consolidated in way movement operations and shipped between major hubs by through movements operations.

The hedonic cost model we employ, in general form, is given by:

$$C = C(\Psi^{WT}(z^{WT}), \Psi^{U}(z^{U}), w, N)$$

where Ψ^{i} represents the ith generic output (i=U,WT) with characteristics z^i, w is a vector of factor prices including labor (l), equipment (e), fuel (f), materials and supplies (m), and way and structures (r), and N is a vector of variables indexing the network and technology.

$$\ln y^{\,i} = \ln y^{i} + \sum_a h_a^i \ln a_a^i$$

The hedonic function, we used is:

where y^i is the generic measure of output (e.g., way-train ton-miles and unit train ton-miles) and a_a^i is the ath attribute pertaining to the ith generic output.

$$\begin{aligned}\ln C_{ft} = {} & a_f + \sum_i a_i \ln y_{fti} + \sum_j b_j \ln w_{ftj} + \sum_n d_n \ln N_{ftn} + qt \\ & + 1/2\left(\sum_i \sum_k A_{ik} \ln y_{fti} \ln y_{ftk}\right) + 1/2\left(\sum_j \sum_m B_{jm} \ln w_{ftj} \ln w_{ftm}\right) \\ & + 1/2\left(\sum_n \sum_l C_{nl} \ln N_{ftn} \ln N_{ftl}\right) + D\,t^2 + \sum_i \sum_j E_{ij} \ln y_{fti} \ln w_{ftj} \\ & + \sum_i \sum_n F_{in} \ln y_{fti} \ln N_{ftn} + \sum_i G_i \ln y_{fti} t + \sum_j \sum_n H_{jn} \ln w_{ftj} \ln N_{ftn} \\ & + \sum_j I_j \ln w_{ftj} t + \sum_n J_n t \ln N_{ftn} + e_{ft}\end{aligned}$$

The empirical specification is the usual translog form:

Estimation proceeds after specification of the variables and substitution of the hedonic output equations into the cost equation. It is estimated by nonlinear Seemingly Unrelated Regressions with symmetry and homogeneity restrictions imposed. These restrictions are:

Symmetry : $A_{ik} = A_{ki}\ \forall\ i\,k,\ B_{jm} = B_{mj}\ \forall\ j\,m,\ C_{nl} = C_{\ln}\ \forall\ n\,l,\ E_{ij} = E_{ji}\ \forall\ i\ j,$
$F_{in} = F_{ni}\ \forall\ n\,i,\ H_{jn} = H_{nj}\ \forall\ j\,n$

Homogeneity : $\sum_j b_j = 1,\ \sum_j B_{jm} = 0\ \forall m,\ \sum_j E_{ij} = 0\ \forall\ i,$
$\sum_j H_{jn} = 0\ \forall\ n,\ \sum_j I_j = 0$

Shepherd's lemma also provides a set of factor share equations given by:

$$s_{ftj} = \frac{\partial \ln C_{ft}}{\partial \ln w_{ftj}} = b_j + \sum_m B_{jm} \ln w_{ftm} + \sum_i E_{ij} \ln y_{fti} + \sum_n H_{jn} \ln N_{ftn} + I_j t + e_{ftj} \qquad \forall j$$

We measure all continuous variables (except for factor shares, time, and fixed effects) with normalizations from sample means to facilitate interpretation.

3.3 Data Sources and Variables

Most of our data are from the R-1 reports of Class 1 railroads reporting to the Interstate Commerce Commission (ICC) and the Surface Transportation Board (STB).[16] These data cover all Class I railroads over the 1983 through 1997 period. In addition, we use the confidential waybill sample and the Association of American Railroads' materials and supply index to supplement some of the data provided in the R-1 reports. All nominal variables were deflated to 1992 levels using the Gross Domestic Product Price Deflator available in the *Economic Report to the President*.

During the time when data are available, there are 240 possible firm years. In 1983, there were 28 railroads. By 1997, that number fell to nine.[17] Most of the reduction in firms has been due to firm consolidation. In Table 3.1, we provide a summary of the firms used in the analysis and acronyms used to identify firms. In Table 3.2, we summarize the firm-years used in the analysis and highlight declassification and consolidation activity from 1983 through 1997.

In developing our model, we use total annual costs as the dependent variable. This variable, and all other variables are defined in Table 3.3. Total annual costs include the sum of expenditures on all factor inputs. Over time, average costs per gross ton-mile for the average firm have declined from 3.351 cents in 1983 to 1.557 cents in 1997 (Table 3.4). This is a reduction in per unit costs of more than 50 percent.

---

[16] The R-1 database was first established in 1978. In 1983, there was a change from betterment to depreciation-based accounting. Using betterment accounting methods, long-term investments often were included as expenses. Under depreciation-based accounting standards, such items are depreciated and only a portion of the investment is included as expenses. The ICC was sunsetted by the ICC Sunset Act of 1995. Some of its activities now are performed by the STB.

[17] These data correspond quite closely with the American Association of Roads *Railroad Facts* (various years). However, there are some differences. Throughout the data, EJE and Long Island are Class I carriers in *Railroad Facts*. However, as the EJE is a switching line and Long Island is a commuter rail line, they were omitted from our data. Other differences between our data reflect differences in the timing of mergers. For example, in 1986 WP and MP were part of the UP merger. It is common as in this case that separate and consolidated reports were filed with the ICC. In our data, we use the UP consolidated reports. Similarly, in 1986, the Southern and NW are reflected in the consolidated report of the NS. In 1987, we have 18 firms in the data. The difference is the BM and DH railroads, each of which were declassified as Class I carriers in 1988 and 1987, respectively. Data are available for each firm in the year declassified, but they are not reflected as Class I railroads in the *Railroad Facts*. Remaining differences are due to missing information in the construction of our variables. These are summarized in Table 3.2.

Two hedonic outputs are used in our analysis. These are way and through gross ton-miles and unit train gross ton-miles, taken directly from the R-1 reports (Table 3.3). Over the 15 years of analysis, there has been considerable change in these variables. Specifically, average way and through gross ton-miles (WTGTM), and unit train ton-miles (UTGTM) have increased dramatically (Table 3.4). This increase likely is reflective of growing industry output, the declassification of smaller firms, and, of course, the massive consolidation movement (The latter two are summarized in Table 3.2). But, the growth, while large for WTGTM, is larger for UTGTM. In particular, over time, average WTGTM increased nearly four times, while average UTGTM increased more than eight times (Table 3.4).

TABLE 3.1. RAILROAD NAME AND ABBREVIATION

Abbreviation	Name
ATSF	Atchison, Topeka & Santa Fe
BLE	Bessemer and Lake Erie
BM	Boston and Maine
BN	Burlington Northern
BO	Baltimore and Ohio
CNW	Chicago and Northwestern
CO	Chesapeake and Ohio
CR	Consolidated Rail Corportation
CSX	CSX Transportation
DH	Delaware and Hudson
DMIR	Duluth, Missabe, and Iron Range
DRGW	Denver, Rio Grande and Western
DTI	Detroit, Toledo and Ironton
FEC	Florida East Coast
GTW	Grand Trunk and Western
ICG	Illinois Central Gulf
KCS	Kansas City Southern
MILW	Milwaukee Road
MKT	Missouri-Kansas-Texas
MP	Missouri Pacific
NS	Norfolk Southern
NW	Norfolk and Western
PLE	Pittsburgh, Lake Erie
SCL	Seaboard Coast Line
SOO	SOO Line
SOU	Southern Railway
SP	Southern Pacific
SSW	Saint Louis and Southwestern
UP	Union Pacific
WP	Western Pacific

TABLE 3.2. SUMMARY OF FIRMS AND YEARS IN DATA

Railroad	#	Years in Market	Reason for Disappearance	Omitted Years[a]
Change of Status				
BLE	2	1983-1984	Lost Class I status	1987-88
BM	6	1983-1988	Lost Class I status	
DH	5	1983-1987	Lost Class I status	
DMIR	2	1983-1984	Lost Class I status	
FEC	9	1983-1991	Lost ClasS I status	
PLE	2	1983-1984	Lost Class I status	
Merger Activity (1983-1997)-Summary of the 12 mergers				
DTI	1	1983	Merged with GTW	1983
MILW	2	1983-1984	Merged with SOO	
NW	2	1983-1984	Merged with SOU to form NS	
SOU	2	1983-1984	Merged with NW to form NS	
MP	3	1983-1985	Merged with UP	
WP	3	1983-1985	Merged with UP	
BO	3	1983-1985	Merged with CO and SCL to form CSX	
CO	3	1983-1985	Merged with BO and SCL to form CSX	
SCL	3	1983-1985	Merged with BO and CO to form CSX	1983-85
MKT	5	1983-1987	Merged with UP	
SSW	7	1983-1989	Merged with SP	
DRGW	11	1983-1993	Merged with SP	
CNW	12	1983-1994	Merged with UP	
ATSF	13	1983-1995	Merged with BN	
BN	13	1983-1995	Merged with ATSF	
SP	14	1983-1996	Merged with UP	1991-92
UP	14	1983-1996	Merged with SP	1988
1997 Firms				
CSX	12	1986-1997	Formed from BO, CO, and SCL (1986)	
NS	13	1985-1997	Formed from SOU and NW (1985)	
UPSP	1	1997	Formed from UP and SP (1997)	
BNSF	1	1996-1997	Formed from BN and SF (1996)	
GTW	15	1983-1997	Merged with DTI (1984)	
SOO	15	1983-1997	Merged with MILW (1985)	1983
CR	15	1983-1997	No Consolidation activity	1992
ICG	15	1983-1997	No Consolidation Activity	
KCS	12	1983-1997	No Consolidation Activity	1992-94

[a] The data were drawn from multiple schedules. In some cases, the schedules were not complete enough to calculate variables (discussed below) or were not present in the raw data. These are years for which firms in the market as Class I firms had missing values and were not used in the estimations.

TABLE 3.3 VARIABLE DEFINITIONS

Variable	Source
Costs	
Real Total Cost	(OPERCOST-CAPEXP +ROIRD +ROILCM+ROICRS)/GDPPD
OPERCOST	Railroad Operating Cost (R1, Sched. 410, ln. 620, Col F)
CAPEXP	Captial Expenditures Classified as Operating in R1 (R1, Sched 410, lines 12-30, 101-109, Col F)
ROIRD	Return on Investment in Road (ROADINV-ACCDEPR)*COSTKAP
ROADINV	Road Investment (R1, Sched 352B, line 31) + CAPEXP from all previous years
ACCDEPR	Accumulated Depreciation in Road (R1, Sched 335, line 30, Col. G)
COSTKAP	Cost of Capital (AAR *Railroad Facts*)
ROILCM	Return on Investment in Locomotives [(IBOLOCO+LOCINVL)-(ACDOLOCO+LOCACDL)]*COSTKAP
IBOLOCO	Investment Base in Owned Loc. (R1, Sched 415, line 5, Col. G)
LOCINVL	Investment Base in Leased Loc. (R1, Sched 415, line 5, Col. H)
ACDOLOCO	Accum. Depr. Owned Loc. (R1, Sched 415, line 5, Col. I)
LOCACDL	Accum. Depr. Leased Loc. (R1, Sched 415, line 5, Col. J)
ROICRS	Return on Investment in Cars [(IBOCARS+CARINVL)-(ACDOCARS+CARACDL)]*COSTKAP
IBOCARS	Investment Base in Owned Cars (R1, Sched 415, line 24, Col. G)
CARINVL	Investment Base in Leased Cars (R1, Sched 415, line 24, Col. H)
ACDOCARS	Accum. Depr. Owned Cars (R1, Sched 415, line 24, Col. I)
CARACDL	Accum. Depr. Leased Loc. (R1, Sched 415, line 24, Col. J)
Generic and Hedonic Outputs	
WTGTM	Way and Through Gross Ton-miles (R1, Sched 755, line 100+line 101, Col. B).
UTGTM	Unit Train Gross Ton-miles (R1, Sched. 755, line 99, Col. B)
WTSS	Way train shipment size. Constructed from Waybill sample.
UTSS	Unit train shipment size. Constructed from Waybill sample.
Factor Prices (all divided by GDPPD)	
Labor Price	Labor Price per Hour (SWGE+FRINGE-CAPLAB) / LBHRS
SWGE	Total Salary and Wages (R1, Sched 410, line 620, Col B)
FRINGE	Fringe Benefits (R1, Sched 410, lns. 112-114, 205, 224, 309, 414, 430, 505, 512, 522, 611, Col E)
CAPLAB	Labor Portion of Cap. Exp. Class. as Operating in R1 (R1, Sched 410, lines 12-30, 101-109, Col B)
LBHRS	Labor Hours (Wage Form A, Line 700, Col 4+6)

TABLE 3.3 **VARIABLE DEFINITIONS**

Variable	Source
Equipment Price	Weighted Average Equipment Price (ROI and Ann. Depr. per Car and Locomotive - weighted by that type of equipment's share in total equipment cost)
Fuel Price	Price per Gallon (R1, Sched 750)
Materials and Supply Price	AAR Materials and Supply Index
Way and Structures Price	(ROIRD+ANNDEPRD)/ MOT
ANNDEPRD	Annual Depreciation of Road (R1, Sched 335, line 30, Col C)
MOT	Miles of Track (R1, Sched 720, line 6, Col B)
Technological and Network Conditions	
Miles of Road	(R1, Sched 700, line 57, Col. C)
Average Length of Haul	RTM / REVTONS
RROWNPER	Percentage of carmiles that are in railroad owned verus private equipment. (Constructed from R-1, Sched 755)
LoadPer	Percentage of loaded carmiles. Constructed from R-1, Sched. 755).
Interlined	Percentage of tons that are interlined. Constructed from QCS form. Report of Freight Commodity Statistics. Total tons interlined/total tons carried.

The hedonic attribute used for each output is shipment size. Shipment sizes were calculated from the waybill statistics for each movement type, railroad, and year. Since the type of movement (i.e., way and through versus unit train) was not available in the waybill data, we proxied movement type by using the convention that a unit train is a multiple-car movement with a shipment size of 50 cars or more. In the R-1 data, there were occasions in which this approach was inappropriate. Specifically, in a few cases, the Waybill yielded non-zero unit train movements (i.e., 50 cars or more), but the R-1 data had zero unit train operations. In these cases, we redefined shipment sizes for way and through operations to reflect waybill statistics. Way and Through Train Shipment Sizes (WTSS) are, of course, much smaller than Unit Train Shipment Sizes (UTSS). The average WTSS were about 1.5 cars per shipment in 1983, falling to 1.144 in 1997 (Table 3.4). On the other hand, average UTSS were about 64 cars in 1983 increasing to slightly more than 93 cars in 1997. With the increases in relative outputs, there is a clear and strong trend toward unit train shipments of larger shipment sizes.

Five factors of production are employed in our cost specification, consisting of labor, equipment, fuel, materials and supplies, and way and structures. Included in the definition of costs is a return on investment for way and structures, and equipment. For the return on investment we used the cost of capital from the American Association of Railroad's publication *Railroad Facts*. Labor prices are defined in terms of total labor costs (including fringe benefits) and are expressed on an hourly basis. Equipment prices are defined as a weighted average of locomotive and car depreciation and return on investment (weighted by expenditures). We first calculate depreciation per locomotive and per car. The expenditures plus a rate of return on investment divided by the number of owned and leased locomotives and cars, respectively, yield the price per locomotive and car. We then form a weighted average of these prices to create an equipment price. Fuel price is expenditures on fuel divided by the number of gallons purchased. Materials and supplies price is reflected by the American Association of Railroad's Materials and Supplies Price Index for railroads operating in the eastern and western portions of the United States. Finally, we include a price for way and structures expressed on a miles-of-track basis. A net investment base is first calculated from the R-1 report. Then a return on investment is applied to derive ROI cost of way and structures. We then add this to an annual depreciation of way and structures and divide the annual cost by miles of track to define the price. Over time, these factor prices have changed, with some particularly large changes — equipment and way and structures prices both have increased by considerable proportions. In particular, equipment prices have increased about 60 percent, while way and structure prices have increased nearly 40 percent. On the other hand, fuel prices have fallen as have materials and supplies. In 1997, fuel prices were approximately one-half of fuel prices in 1983.

Six variables index the technology that can be classified as operating and/or network variables. These include miles of road, average length of haul, the percentage of car-miles that are railroad-owned (versus shipper owned), percentage of miles traveled that are loaded, the percentage of interlined traffic (the percentage of tons interlined divided by total tons carried), and a time trend to allow for technological change. Miles of road measures the size of the network and generally has been included in cost models and is expected to have an increasing effect on costs. Average length of haul (the average distance a ton travels) also generally has been included in cost models and should have a decreasing effect on costs. The percentage of car-miles that are railroad owned is included in this specification (unlike others) to reflect the fact that shippers commonly ship commodities in their own cars. As this percentage increases, it should have a negative influence on costs due to the increased potential of circuitous routing of private cars. The percentage of miles that are loaded also is included in the specification. As the percentage of loaded miles increase, costs should decrease due to better equipment utlization. We also include the percentage of traffic that is interlined. The interlining of movements requires extra switching and time delays. As such, we expect that increases in interlining will have an increasing effect on costs. Finally, we include a time trend to reflect technological change. Over time, there have been many innovations in the industry, some of which are not reflected in the specification (e.g., see MacDonald (1998), and Bitzan and Keeler (2003) who provide extensive discussions). Improvements in technology should have a reducing effect on costs.

Over the range of analysis, there have been significant changes in these variables. Average miles of road per firm (MOR) has more than doubled as a result of mergers and declassifications (Table 3.4). However, unlike industry output, industry network size has fallen. That is, industry network size has fallen, but the firms in the data have larger networks. Associated with larger networks have been longer lengths of haul. Average length of haul has increased from an average of 371 miles in 1983 to 490 miles in 1997 (Table 3.4). The percentage of railroad owned car-miles has fallen from about 67 percent to 57 percent, while the percentage of loaded miles has increased slightly from 56 percent to 59 percent (Table 3.4). Finally, associated with mergers, there is less interlined traffic. That is, with mergers, railroads are better able to provide service without interchange, with the result that the percentage of interlined traffic has fallen from 71 percent to about 56 percent over the period of analysis (Table 3.4).

TABLE 3.4 SUMMARY STATISTICS 1983 AND 1997

	1983			1997		
Variable	Mean	Min	Max	Mean	Min	Max
Cost/GTM	3.351	1.859	8.772	1.557	1.179	1.876
WTGTM	47.556	0.967	147.663	187.466	20.858	525.851
UTGTM	11.812	0.000	177.566	94.910	2.131	328.554
WTSS	1.466	1.011	6.378	1.144	1.035	1.244
UTSS	63.742	0.000	107.176	93.180	81.223	102.744
wL-Labor	25.117	13.762	31.863	26.541	24.325	30.052
wE-Equip	23290.38	2372.07	56745.56	37501.17	7440.14	62106.16
wF-Fuel	1.170	1.028	1.326	0.597	0.544	0.636
wM-Mtl&Sup	189.513	185.483	194.641	179.757	157.569	207.493
wW-Way&Struc	46397.72	11706.21	108037.8	65398.48	41556.69	83399.8
MOR	5952.36	204.000	28068.0	13518.99	659.00	34946.0
ALH	370.991	50.197	718.294	489.580	64.096	935.368
OWN%	67.591	48.943	99.717	57.253	44.517	73.836
LOAD%	56.878	49.985	65.566	59.156	54.422	64.848
INTER%	71.275	34.543	96.043	55.739	29.456	85.246

3.4 Econometric Results

We estimate two versions of this model. The first set of results excludes fixed effects, while the second specification allows for fixed effects. Caves, Christensen, Tretheway, and Windle (1985) appear to be the first to estimate such a model. They note that until their paper was published, literature had mixed findings with respect to the level of economies of density. They conclude that "...the strongest defensible statement at this point is that there is no strong evidence against the hypothesis of increasing returns to density." They further state that "...the lack of clear-cut findings regarding economies of density results from the failure to account for unobserved network effects." They model unobserved network effects through the inclusion of fixed effects. They find that once such controls are introduced to the estimation, they get nearly identical results with respect to scale as did previous studies, but find that there are substantial economies of density at every level of output. Whether network effects or other systematic firm-specific effects are present, we find that the inclusion of fixed effects is mandated on statistical grounds.[18] Indeed, exclusion of these effects may result in bias.

The results of the model estimated with nonlinear, seemingly unrelated, regressions with fixed effects is provided in Table 3.5.[19] We do not present the fixed effects in this table. They are presented in Table 3.6. The specification without fixed effects is not presented, but can be provided on request. Generally, the model without fixed effects yields qualitatively similar results as those with fixed effects. However, some of the magnitudes and even the qualitative results are different. For example, the linear term on average length of haul is negative (as expected) in both specifications. In the results presented it is not statistically significant, while in the model without fixed effects it is much larger in magnitude and statistically significant. At mean values, the linear sum of the scale measures (i.e., the sum of the coefficients on WTGTM and UTGTM) are each less than one, but, the sum is smaller in the fixed effect specification. This sum is central in debates concerning the level of scale economies in the technology. Each of the specifications suggest that there are ray scale economies in the technology. Throughout the rest of this section, we use the fixed effect specification.

The model fits the data extremely well and is consistent with comparable previous work. The adjusted R^2 for the cost equation is in excess of .99. For the labor, equipment, fuel, and material and supplies equations (the way and structures equation is the omitted share) adjusted R^2 are .67, .30, .76, and .41, respectively.

Interpretation of the coefficients is relative to the average firm in the sample. This treatment allows the interpretation to be captured mainly in linear terms. In this regard, the coefficients largely are in the range of *a priori* expectations. The shipment size coefficients each have the expected signs. However, for way and structures, shipment sizes are not statistically significant. As noted in Table 3.4, the range of shipment sizes

---

[18] The fixed effects are captured through the inclusion of intercept dummy variables. Over the period of analysis there were a number of mergers. If a merger occurred, we incorporated the merger effect by defining the combined firm as a new firm in the data. The information provided in Table 3.2 was used to defined the mergers.

[19] We did not estimate a three-stage least squares system. However, Bitzan (1999) estimates a similar model in which he did specification tests for endogeneity, finding that a model similar to this one can be estimated using SUR without statistically significant bias.

for non-unit train traffic is not large and has become smaller with time.[20] For unit train traffic, the coefficient is negative and statistically significant. As noted in Table 3.4, average shipment size was large in 1983 and has grown with time, from about 64 cars to more than 93 cars in 1997. This suggests that innovations in railroad pricing and savings have had a strong negative effect on costs.

The generic output terms (*WTGTM* and *UTGTM*) have the expected signs and relative magnitudes. Specifically, a 1 percent in *WTGTM* and in *UTGTM* increase costs by .417 and .092 percent respectively (using a time reference of zero). These are quite comparable to Bitzan (1999) who estimates a similar model. The coefficients also reflect coefficients on the hedonic outputs (in the hedonic model the generic measures are normalized to one). In Table 3.5, we represent the hedonic outputs as *H1* and *H2* for way and through output and for unit train output, respectively.

The factor price coefficients are each positive in sign (factor prices increase costs) and of the relevant magnitudes (for each factor they should reflect sample averages of cost share). Miles of road increases costs as expected and is commonly found. A 1 percent increase in MOR increases costs by .758. Given that average railroad miles of road have been increasing, this would be expected to put upward pressure on railroad costs *ceterus paribus*, but these increases are offset by accompanying increases in the level of traffic and changes in network characteristics. Average length of haul has the expected sign, but it is not statistically significant.[21] The percentage of car-miles in railroad-owned equipment versus private-owned equipment is statistically significant and has a negative influence on costs. A 1 percent increase in the percentage of owned railroad costs reduces costs by an estimated .209 percent. The percentage of car-miles that are loaded does not have a statistically significant effect in the linear term. The percentage of cars that are interlined, however, does have a statistically significant effect. In this case, a 1 percent change in the percentage of interlined traffic increases costs .387 percent. This seems to be a large effect and is particularly important given the change over time in this variable due to consolidation in the industry. In particular, and as noted in Table 3.4, the average value of this variable has fallen, and fallen significantly over the range of the data, from 71 percent in 1983 to 56 percent in 1997. The final coefficient in linear terms is the time trend. As expected, the passage of time reduces costs due to non-measured innovation. In this case, average railroad costs are falling about 2.67 percent per year. There are many second order terms (interactions in the model). However, while there are a number of important second order effects, we do not provide an in depth discussion of these interactions. Generally, the technological variables exhibit considerable statistical significance in the second order terms. There seem to be complementarities between the hedonic output terms. That is, the elasticity of costs for one output measure is decreasing in the other output measure. The effects of the technological variables seem to differ across hedonic measures in a statistically significant fashion.

---

[20] The relative small range and "range of change" in this variable may help to explain the lack of statistical significance. In the non-fixed effect specification, it was larger in magnitude and statistically significant. With the inclusion of fixed effects with little change over time, the effects of way and through shipment sizes may be captured in the fixed effects.

[21] In the authors' experience this effect is a common finding with the inclusion of fixed effects. In this case, as in our previous work, the effect of ALH is negative and statistically significant in models without fixed effects. The inclusion of fixed effects may change the sign and remove its statistical significance.

TABLE 3.5 PARAMETER ESTIMATES

Variable	Estimate	Variable	Estimate	Variable	Estimate
Constant	-0.355*	.5*H2*H2	0.037**	ALH*own%	0.014
	(0.184)		(0.015)		(0.324)
NoUnit	0.026	.5*wL*wL	0.105***	ALH*Load%	0.804*
	(0.094)		(0.013)		(0.431)
WTSS	-0.068	wL*wE	-0.009*	ALH*inter%	-0.203
	(0.164)		(0.005)		(0.218)
UTSS	-2.047***	wL*wF	-0.012***	ALH*yr	0.015
	(0.688)		(0.003)		(0.013)
WTGTM	0.417***	wL*wM	-0.015	.5*own%*own%	-1.501**
	(0.123)		(0.013)		(0.692)
UTGTM	0.092**	.5*wE*wE	0.029***	own%*Load%	-0.125
	(0.040)		(0.005)		(1.176)
wL	0.352***	wE*wF	-0.003**	own%*inter%	-0.444*
	(0.006)		(0.001)		(0.256)
wE	0.157***	wE*wM	-0.000	own%*yr	0.033**
	(0.005)		(0.007)		(0.016)
wF	0.057***	.5*wF*wF	0.049***	.5*Load%*Load%	-1.656
	(0.002)		(0.004)		(1.659)
wM	0.198***	wF*wM	-0.020***	Load%*inter%	0.590
	(0.008)		(0.005)		(0.856)
MOR	0.758***	.5*wM*wM	0.090***	Load%*yr	-0.000
	(0.120)		(0.019)		(0.051)
ALH	-0.028	.5*MOR*MOR	0.027	.5*inter%*inter%	0.539
	(0.163)		(0.142)		(0.371)
OWN%	-0.480**	MOR*ALH	0.231	inter%*yr	-0.020**
	(0.224)		(0.207)		(0.009)
LOAD%	-0.209	MOR*own%	0.743***	.5*yr*yr	-0.000
	(0.552)		(0.268)		(0.000)
INTER%	0.387**	MOR*Load%	-0.038	H1*wL	0.022***
	(0.155)		(0.504)		(0.008)
YR	-0.026**	MOR*inter%	-0.240*	H1*wE	0.027***
	(0.010)		(0.132)		(0.006)
.5*H1*H1	0.366***	MOR*yr	-0.008	H1*wF	-0.003
	(0.123)		(0.009)		(0.002)
H1*H2	-0.111***	.5*ALH*ALH	-0.101	H1*wM	0.012
	(0.029)		(0.335)		(0.011)

TABLE 3.5 PARAMETER ESTIMATES (continued)

Variable	Estimate	Variable	Estimate	Variable	Estimate
H2*wL	-0.004**	own%*wM	-0.079***	H1*own%	-0.602**
	(0.001)		(0.022)		(0.241)
H2*wE	0.009***	Load%*wL	0.070**	H1*Load%	-0.194
	(0.001)		(0.029)		(0.497)
H2*wF	0.001***	Load%*wE	-0.010	H1*inter%	0.128
	(0.000)		(0.026)		(0.157)
H2*wM	-0.010***	Load%*wF	-0.005	H1*yr	-0.001
	(0.002)		(0.008)		(0.008)
MOR*wL	0.000	Load%*wM	-0.103**	H2*MOR	0.118***
	(0.008)		(0.040)		(0.033)
MOR*wE	-0.038***	inter%*wL	0.027***	H2*ALH	-0.017
	(0.007)		(0.008)		(0.027)
MOR*wF	-0.004*	inter%*wE	0.010	H2*own%	-0.061
	(0.002)		(0.007)		(0.048)
MOR*wM	-0.016	inter%*wF	-0.002	H2*Load%	0.128
	(0.012)		(0.002)		(0.141)
ALH*wL	-0.066***	inter%*wM	-0.016	H2*inter%	0.031
	(0.008)		(0.012)		(0.028)
ALH*wE	-0.024***	yr*wL	-0.003***	H2*yr	0.002
	(0.008)		(0.000)		(0.003)
ALH*wF	0.037***	yr*wE	-0.004***		
	(0.002)		(0.000)		
ALH*wM	0.051***	yr*wF	0.000***		
	(0.011)		(0.000)		
own%*wL	0.061***	yr*wM	0.002**		
	(0.016)		(0.000)		
own%*wE	0.045***	H1*MOR	-0.162		
	(0.014)		(0.111)		
own%*wF	-0.013***	H1*ALH	-0.114		
	(0.004)		(0.173)		

TABLE 3.6 FIXED EFFECTS (BN=BASE)

Variable	Estimate	Standard Error
ATSF	0.5127***	0.153
BLE	0.7885*	0.447
BM	0.8013**	0.306
BO	0.8900***	0.234
CNW	0.6264***	0.222
CO	0.9285***	0.238
CR	0.7377***	0.164
CSX	0.4572**	0.203
DH	0.1425	0.319
DMIR	0.6864	0.553
DRGW	0.5339**	0.252
FEC	1.0564***	0.313
GTW	0.920***	0.256
ICG	0.8035***	0.236
KCS	0.5756**	0.252
MILW	0.7330***	0.261
MKT	0.3166	0.287
MP	0.5317***	0.186
NS	0.5008***	0.165
NW	0.7971***	0.197
PLE	0.5633	0.360
SOO	0.2805	0.283
SOU	0.6819***	0.235
SP	0.5514***	0.168
SSW	0.0733	0.268
UP	0.4623***	0.169
WP	0.2091	0.293
MERGERS		
GTW1=GTW+DTI	0.9510***	0.253
SOO1=SOO+MILW	0.4321*	0.229
UP1=UP+MP+WP	0.1133	0.097
UP2=UP+MKT	0.0985	0.093
SP1=SP+SSW	0.3146**	0.149
SP2=SP+DRGW	0.1459	0.130
UP3=UP+CNW	0.1519	0.128
BN1=BN+ATSF	-0.136	0.163
UP4=UP+SP	-0.005	0.200
CSX	N.A. (see above)	
NS	N.A.(see above)	

A *, ** and *** indicate statistical significance at the 1, 5 and 10 percent levels.

3.5 Simulations

We use this model to simulate movement costs and compare them with URCS-generated movement costs. In doing so, we use the waybill sample to identify movements for farm products, coal, and chemicals. For some years the waybill sample contains URCS-generated costs, which can be expressed on a ton-mile basis. We use the movement data to identify the added way and through train and the unit train ton-miles. In this regard, we calculate from the waybill, the added net ton-miles. We convert the net ton-miles to gross ton-miles using railroad system averages on the ratio of gross ton-miles to revenue ton-miles. We then add the shipment ton-miles to the railroad's traffic base, calculate incremental costs of the movement, and express it on a ton-mile basis. In mapping the waybill shipment characteristics to the railroad costs, we make an arbitrary distinction between way and through train movements and unit train movements analogously to that used in calculating average shipment size. That is, any movement involving more than 50 cars is classified as unit train movement, and all others are classified as way and through movements.

Our calculations only include the added ton-miles. They do not make any adjustments in the other variables of the translog. That is, theoretically, the added cost of a movement can be written as:

$$\Delta C = C(Q + \Delta Q; X + \Delta X) - C(Q; X)$$

Where *C()* is the cost function, *Q* is output, and *X* is all of the remaining explanatory variables. Theoretically, some of the remaining explanatory variables can change with movement characteristics. However, these are generally system averages (or are variables which do not change), and as a result, the change is quite small and is ignored for these purposes. In our calculation of incremental costs, we use:

$$\Delta C = C(Q + \Delta Q; X) - C(Q; X)$$

In applying our approach, we use the 1996 Waybill sample for Farm Products, Chemicals and Coal. From this sample, we calculate net ton-miles for each movement and calculate the URCS cost per ton-mile. We then use the net ton-mile figure along with shipment type (i.e., way and through versus unit) and add that to the traffic base of the railroads. We then simulate the added costs per ton-mile as described above.

The simulations are presented in Table 3.7, showing average costs per ton-mile, by commodity, railroad, and shipment type, and showing the associated movement characteristics. Costs per ton-mile are shown as simulated by our translog cost function and as estimated by URCS. Throughout the entire table, costs generated by URCS are higher than the costs generated by translog. In some cases, the difference in per unit costs are quite high.

In addition to differences between translog and URCS costs, sizable differences exist between way and through costs per ton-mile and unit train costs per ton-mile. This is true for the translog simulations and the URCS simulations.

Finally, our plots of the results along with the econometric results, suggest that the translog is exceptionally good at explaining system costs. However, our inspection of the plots suggests there is little variation in costs, given the railroad and the shipment type. Stated differently, the econometric specification presented may well provide good estimates of the average cost of individual railroads across shipment types, but costs do not seem to vary much across shipments in a railroad and shipment classification (i.e., with the way/through or unit classifications). That is, the translog cost function does not do well for individual shipment costing. For this reason, along with the various short-comings of URCS, we present an alternative model in the following section of the report. With this model, we begin with disaggregate data and develop theoretically strong estimates of costs, with the added appeal of the costs being applicable to individual movement characteristics.

TABLE 3.7 URCS AND TRANSLOG SHIPMENT COSTS FOR CHEMICAL, COAL, AND FARM PRODUCTS

Commod	Type	RR	N	URCS cost/tm	Translog cost/tm	Ton-miles	Tons/car	Distance	# of Cars
CHEM	W&T	BN	2677	2.705	0.886	331999	80.75	1063.80	2.88
CHEM	W&T	CR	932	3.225	1.636	74270	74.17	511.91	1.06
CHEM	W&T	CSX	4062	3.098	1.218	141909	80.16	515.52	3.17
CHEM	W&T	GTW	28	2.493	1.077	94346	90.54	288.32	1.46
CHEM	W&T	ICG	597	2.810	0.128	90956	94.11	391.16	1.29
CHEM	W&T	KCS	369	2.802	0.899	71293	82.87	445.31	1.28
CHEM	W&T	NS	2179	2.566	1.036	145578	77.47	562.54	1.74
CHEM	W&T	SOO	241	3.591	0.447	58713	85.04	343.83	1.10
CHEM	W&T	SP	1645	3.125	0.956	129684	65.46	1168.54	1.07
CHEM	W&T	UP	2134	2.345	1.349	399957	85.63	963.61	2.48
CHEM	Unit	BN	11	1.220	0.550	10587888	100.33	836.36	72.54
CHEM	Unit	CSX	180	5.605	0.728	453065	61.90	41.68	79.80
CHEM	Unit	NS	Unit	1.761	0.964	1664405	104.67	151.00	52.00
CHEM	Unit	UP	23	1.078	0.419	12191059	98.54	924.30	65.82
COAL	W&T	BN	390	3.030	0.886	1060922	98.69	319.74	32.22
COAL	W&T	CR	159	2.205	1.636	1728946	94.86	327.79	25.41
COAL	W&T	CSX	1289	2.753	1.218	1347644	93.55	394.20	16.02
COAL	W&T	GTW	3	1.321	1.077	3007645	108.33	355.00	31.33
COAL	W&T	ICG	9	1.861	0.128	1504783	97.67	177.11	47.22
COAL	W&T	NS	11003	2.144	1.036	253512	100.34	386.92	4.87
COAL	W&T	SOO	2299	3.030	0.447	93187	104.68	248.56	2.56
COAL	W&T	UP	154	2.261	1.349	2378842	98.22	440.89	27.42
COAL	Unit	BN	3259	1.041	0.550	14704154	108.87	653.36	107.69
COAL	Unit	CR	1898	1.468	1.324	7429726	99.99	329.16	97.78
COAL	Unit	CSX	5390	1.440	0.728	8187702	102.93	381.62	93.92

COAL	Unit	ICG	424	1.357	0.288	5432008	102.02	276.91	91.09
COAL	Unit	KCS	124	1.726	0.451	3243670	100.47	146.56	87.97
COAL	Unit	NS	2403	1.466	0.964	6918621	104.54	341.00	90.55

TABLE 3.7 URCS AND TRANSLOG SHIPMENT COSTS FOR CHEMICAL, COAL, AND FARM PRODUCTS

Commod	Type	RR	N	URCS cost/tm	Translog cost/tm	Ton-miles	Tons/car	Distance	# of Cars
COAL	Unit	SOO	341	1.272	0.727	4614155	104.37	207.09	105.34
COAL	Unit	UP	459	1.249	0.419	10162222	101.54	482.99	96.15
FARM	W&T	BN	4151	2.445	0.886	1631211	73.35	1197.19	10.14
FARM	W&T	CR	495	3.134	1.636	560765	56.99	659.25	5.69
FARM	W&T	CSX	961	2.410	1.218	1120832	84.06	664.16	8.33
FARM	W&T	GTW	39	3.580	1.077	174858	98.76	182.46	6.71
FARM	W&T	ICG	494	2.046	0.128	1776941	95.57	378.26	21.67
FARM	W&T	KCS	404	2.655	0.899	1629844	71.93	593.76	13.61
FARM	W&T	NS	1762	2.272	1.036	1522393	92.09	555.82	14.51
FARM	W&T	SOO	2217	2.989	0.447	596991	98.19	464.30	6.51
FARM	W&T	SP	395	2.611	0.956	954799	58.39	980.83	9.89
FARM	W&T	UP	1219	2.388	1.349	1771617	91.39	670.47	16.29
FARM	Unit	BN	549	1.308	0.550	12894461	99.34	1255.62	58.33
FARM	Unit	CR	7	1.523	1.324	11546638	100.90	619.86	76.42
FARM	Unit	CSX	274	1.520	0.728	9765637	94.72	737.74	63.64
FARM	Unit	ICG	40	1.503	0.288	9699607	93.54	732.83	74.67
FARM	Unit	KCS	22	1.661	0.451	8570785	98.70	647.82	67.31
FARM	Unit	NS	126	1.642	0.964	6666814	102.13	491.52	62.77
FARM	Unit	SOO	19	1.339	0.727	6323684	99.27	531.47	60.31
FARM	Unit	SP	18	2.571	0.772	6186654	61.74	634.44	62.22
FARM	Unit	UP	528	1.301	0.419	15606627	98.49	885.97	80.14

4. NEW EMPIRICAL INDUSTRIAL ORGANIZATION

In this section, we present the NEIO model and results. As discussed earlier, the primary benefit of the NEIO approach is that it begins with disaggregate data. In particular, the dependent variable is the rate attached to a specific movement. This is in contrast to the URCS model and the translog specifications, which begin with annual system aggregate cost data. While the NEIO has been used widely (Appendix B), the reader should note that this approach has not been used to uncover costs of specific waybill movements. The results presented here should be viewed as a first attempt, and refinements are most assuredly warranted.

4.1 Estimating Costs through Pricing Relations

Using the NEIO approach, we specify our model for estimating commodity-specific rail rates following papers by Bresnahan (1989), with specific incorporation of the models used by MacDonald (1987, 1989) in his modeling of waybill rates.[22] Hence, in a similar manner, we define the rate charged by the railroads to haul a specific commodity as follows:

$$P_i = MC - (\partial P / \partial Q) Q_i \cdot \theta \qquad (1)$$

In equation (1), P_i denotes the rate charged to haul a specific commodity, MC denotes marginal cost, Q_i refers to quantity of the commodity to be hauled by each railroad, and θ is a market power indicator. Multiplying each side of the equation (1) by Q_i, and dividing by Q, yields the following:

$$\frac{PQ_i}{Q} = MC\frac{Q_i}{Q} - \frac{\partial P}{\partial Q}\frac{Qi^2}{Q^2}Q\theta \qquad (2)$$

In the above equation, it should be noted that the $\frac{Q_i^2}{Q^2}$ term is equivalent to the square of each firm *i*'s market share, and hence by adding equation (2) across all *i*'s, this term will be replaced by the Herfindahl index, denoted as H.

$$P = MC - H\frac{\partial P}{\partial Q}Q\theta \qquad (3)$$

By multiplying the right hand side of equation (3) by $\frac{P}{P}$, a term defining the reciprocal of elasticity of demand emerges, $\frac{\partial P}{\partial Q}\frac{Q}{P}$, and is replaced by the symbol 1/ε,

$$P = MC - H\theta\frac{1}{\varepsilon}P \qquad (4)$$

---

[22] The method used by Azzam to decipher the market power and cost efficiency effects resulting from increased concentration in the beef packing industry provides a useful tool for our current analysis.

Rearranging equation (4) and taking logs of both sides of the equation, generates the following:

$$\log P = \log MC - \log(1 + \frac{Hq}{e}) \qquad (5)$$

which is approximately equal to:

$$\log P = \log MC - \frac{Hq}{e} \qquad (6)$$

Hence, from equation (6) it is plain to see that we model the rate, for each separate commodity, as a function of a set of cost variables that describe MC (the first term in equation (6), and a set of demand variables that describe the second term in equation (6)). So equation (6) can be represented as:

$$\log P \approx X_C^T b + X_M^T d \qquad (7)$$

where X_C^T is the transpose of a vector of cost variables that describe MC, β is a coefficient vector for the associated cost variables, X_M^T is the transpose vector of markup variables, and δ represents the coefficient vector for the markup variables. Using equation (7), predicted values for rate, $\hat{P}$, MC variables, $X_C^T\hat{b}$, and markup variables, $X_M^T\hat{d}$, then can be extracted. Thus, through the estimation of equation (7), we are able to generate values of marginal cost through pricing relations. In other words, since one can not observe or estimate marginal cost directly, we estimate rates using variables that we know MC depend on, and produce estimates of MC in this manner.

4.2 Data Description

The data used in our analysis were obtained from the STB's Annual Waybill Sample from 1983 through 2000. The Annual Waybill Sample represents 1 percent of all rail shipments each year. It is a stratified random sample, meaning that the sampling probabilities increase as the number of carloads in a shipment increase.[23] Hence, to account for the fact that the sample is stratified, each data observation from the Waybill is adjusted using its sampling probability.[24] All of the data described in the ensuing paragraphs were extracted from the Waybill sample for each specific commodity, and for each year.

The dependent variable (rate) used in our estimation is RPTM (revenue per ton-mile). The variables used to derive RPTM, *revenue, tons,* and *miles,* were each acquired from the Waybill sample. *Revenue* is defined as the total freight line-haul revenue in dollars, from origin to destination. *Tons* is billed weight in tons. *Miles* is equal to "short line miles," a measure defined as the shortest rail route over which carload traffic can be moved. Thus, multiplying *tons* by *miles* yields a measure of output for describing the quantity of a commodity hauled by the railroad between a specific origin and destination, called *ton-miles*. Dividing *revenue* by *ton-miles* gives us the dependent variable for rates, RPTM.

---

[23] MacDonald (1987).

[24] For a more complete description of waybill data refer to Wolfe (1986) and Wolfe (1991).

Many variables could conceivably influence the cost per ton for the shipment of a certain commodity. To reflect these factors, we use MILES, NUMCAR, and TONSCAR as explanatory variables. MILES was obtained from the Waybill sample and is defined in the previous paragraph. Theoretically, costs per ton-mile of shipping a commodity should decrease as MILES increase. The size of shipment is an important factor for determining costs. The variable NUMCAR measures the total number of cars in the shipment, and hence is one way to gauge the size of each shipment. Similarly, the tonnage per car in the shipment, TONSCAR, also provides a magnitude regarding the shipment size. Both variables are included in the estimation and it is hypothesized that an increase in either will induce a decrease in the dependent variable, RPTM.

We include RRCOMP to capture the effect of intramodal competition. RRCOMP is defined as the reciprocal of the Herfindahl index. The market share components for the Herfindahl index were calculated at the county level. This variable serves as a measure of the level of competition in an area, as it embodies the number of competing railroads in the area and the size (market power) of each. Intuitively then, RRCOMP should exhibit a negative relationship with RPTM. Another measure of competition, MIWATER, is included as an explanatory variable. We specify this variable as a proxy for intermodal competition, specifically from water transport (barge). MIWATER measures the distance from the originating point to the nearest available water transport, in miles. Theory suggests that as the distance from water increases, (making water transportation less available and less competitive), the rate charged to shippers should increase.

A time variable, labeled TREND, is included in the estimation to capture time effects, such as technological progress. INTRA is a dummy variable set equal to 1 for intrastate shipments. According to MacDonald, some states still exercised intrastate regulation of shipments during part of this time period. This variable is intended to capture any effects of such regulation[25]. Because the demand for rail transport may vary by seasons, depending on the commodity to be transported, quarterly dummy variables were also added. They are denoted as Q1,Q2, Q3, Q4, with Q1 designated as the base.

In estimating each equation, a dummy variable named ORTR also is used. This dummy variable represents each origin-destination pair between which a commodity is shipped, defined by state. That is to say, ORTR is defined as a group by using the state in which the shipment originated and the state in which the shipment terminated. Hence, this dummy variable was included to capture variation (the "fixed effects") of each unique origin-destination pair.

4.3 Empirical Results

All data were screened for outliers, and therefore the ensuing estimation should accurately reflect the relationship between the dependent and the explanatory variables.[26] The variables described in the preceding paragraphs will now be used to estimate equation (6). In this regard, we write the final model to be estimated for each commodity in the following form:

---

[25] MacDonald (1987).

[26] In screening for outliers, extreme and unreasonable values were identified as those data points that were below (above) the one-half percentile (99.5 percentile) mark.

$$\begin{aligned}\ln RPTM &= b_0 + b_1 \ln MILES + b_2 \ln NUMCAR + b_3 \ln TONSCAR + b_4 MIWATER \\ &+ b_5 RRCOMP + b_6 INTRA + b_7 Q2 + b_8 Q3 + b_9 Q4 + b_{10} TREND + b_{11} ORTR + e_{it}\end{aligned} \tag{8}$$

Six commodities were used in the estimation, four which are defined at the four-digit STCC level and two which are defined at the two-digit STCC level. Commodities specified with a four-digit STCC code are wheat (1137), corn (1132), soybeans (1144), and barley (1131), while those defined by a two-digit STCC code are coal (11) and chemicals (28). The empirical results from the estimation of equation (8) are displayed in Table 4.1.

TABLE 4.1. NEIO COEFFICIENT ESTIMATES

Variable	Wheat	Corn	Soybeans	Barley	Coal	Chemicals
MILES	-0.5844***	-0.5217***	-0.6037***	-0.4515***	-0.5330***	-0.5735***
	(0.0047)	(0.0050)	(0.0059)	(0.0161)	(0.0014)	(0.0014)
NUMCAR	-0.0531***	-0.0412***	-0.0304***	-0.0308***	-0.0612***	-0.0645***
	(0.0011)	(0.0009)	(0.0020)	(0.0020)	(0.0015)	(0.0015)
TONS/CAR	-0.2247***	-0.5850***	-0.8297***	-0.7178***	-0.1494***	-0.1616***
	(0.0324)	(0.0255)	(0.0359)	(0.0564)	(0.0021)	(0.0022)
MIWATER	0.0009***	0.0003***	0.0008***	0.0006***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)
RRCOMP	-0.0143***	-0.0112***	-0.0075	-0.0313***	-0.0511***	-0.0510***
	(0.0029)	(0.0024)	(0.0048)	(0.0050)	(0.0008)	(0.0008)
INTRA	0.0571***	0.1052***	0.0470**	0.1029***	0.0559***	0.0555***
	(0.0102)	(0.0122)	(0.0224)	(0.0128)	(0.0056)	(0.0058)
QTR2	0.0107**	0.0026	0.0023	0.0036	0.0012	0.0014
	(0.0047)	(0.0035)	(0.0075)	(0.0075)	(0.0017)	(0.0017)
QTR3	0.0146***	-0.0033	0.0055	0.0023	-0.0040**	-0.0043**
	(0.0044)	(0.0038)	(0.0074)	(0.0067)	(0.0017)	(0.0018)
QTR4	0.0032	-0.0018	0.0301***	-0.0109	-0.0097***	-0.0094***
	(0.0048)	(0.0035)	(0.0063)	(0.0068)	(0.0017)	(0.0017)
TREND	-0.0141***	-0.0155***	-0.0127***	-0.0256***	-0.0277***	-0.0278***
	(0.0004)	(0.0003)	(0.0007)	(0.0007)	(0.0001)	(0.0001)
CONSTANT	6.0049***	7.2925***	8.5853***	7.7049***	6.1043***	6.4132***
	(0.1496)	(0.1224)	(0.1683)	(0.2702)	(0.0135)	(0.0137)

Observations	77598	90666	25177	16692	574729	579162
Adj-R-squared	0.76	0.75	0.80	0,82	0.62	0.65

A *, ** and *** indicate statistical significance at the 10, 5, and 1 percent levels.

The results generated from estimation of Equation 8 are informative. First of all, it is important to note that the coefficient estimates for nearly all variables from Equation 8 are significant, (except the quarterly dummy variables and one RRCOMP coefficient in the equation for barley), and nearly all the estimates are significant at the 1 percent level. Furthermore, each coefficient estimate in the table displays the correct hypothesized sign. The overall measure of fit for the model, measured by the adjusted R-squared, varies in magnitude by commodity, from .62 to .82. Commodities from the four-digit STCC level were more narrowly defined and, hence, the adjusted R-squared for these commodities tends to be the highest. Further decomposition of coal and chemicals to a higher STCC digit level commodity likely would yield a higher measure of the adjusted R-squared, by narrowing the definition of these broad commodities.

For all commodities, the variables MILES, NUMCAR, and TONS/CAR are estimated to have a negative impact on RTM. Hence, as these shipment size and distance variables increase, the revenue per ton-mile is estimated to decrease. This relationship coincides with theory and is generally expected. Interestingly, the magnitude of the coefficient estimates for MILES and NUMCAR do not vary much across commodities, (-0.45 to -0.60 and -0.03 to -0.06, respectively). However, the coefficient estimates for TONS/CAR do vary significantly in magnitude across commodities, ranging from -0.14 for coal to -0.82 for soybeans. The next highest values for the TONS/CAR coefficients also were associated with farm commodities, namely corn and soybeans.

MIWATER is positive and highly significant for all commodities. Hence, the further the originating point is from water transport and barge competition, the more likely a shipper will observe increases in rates. Again, the coefficient estimates for MIWATER are largest for the farm commodities, wheat, soybeans, and barley, indicating that farm commodity origins located further from water transport are subject to increased rates.

RRCOMP is negative and significant for all commodities except soybeans, and it is nearly significant for soybeans (it was significant at the 11 percent level). In contrast to the estimates for MIWATER and TONS/CAR variables, the estimates of RRCOMP do not display the highest values for farm commodities. Instead, coal and chemicals are the commodities presumably to be most affected by increased rail competition. This is because the majority of shipments for both commodities are done via rail transportation. So, it would seem logical that shippers of these commodities that are located in areas with increased concentration would observe higher rates.

The variable INTRA was included to capture the effects of state regulation on rates. In our estimation, INTRA is positive and highly significant for all commodities. Since INTRA reflects the regulation of intrastate shipments, it appears that state level regulation may have a positive effect on rates.

The estimated coefficient for the time variable, TREND, also displays significance across commodities, and is negative. Therefore, for each commodity classification estimated, the time variable captures a decreasing trend in RPTM over each year. Corresponding to theory, this negative relationship between time and rates could represent advances in technology, which would assuredly result in decreasing rates.

4.4 Marginal Cost Estimates

Using the NEIO approach described earlier, we were able to derive estimates of marginal costs, for each commodity, using our estimation results from Equation 8. Figure 4.1 displays graphs of the marginal cost (MC) estimates over time for the four farm commodities studied in this paper, which are wheat, corn, soybeans, and barley. Both the NEIO marginal costs estimates derived in this paper and the URCS cost estimates are shown in each graph.[27] The data points in the graphs represent the average (mean) marginal cost estimates by year, using either the NEIO or the URCS approach.

Marginal costs decreased with time for all commodities. Similarly, both the NEIO and URCS approaches predicted marginal cost values that decrease with time, coinciding with economic theory. The most striking result from these graphs is that in all cases, the NEIO approach yielded marginal cost estimates greater than those generated by URCS. Wheat displays the most dramatic decrease over time, while the marginal cost for corn seems to decrease only slightly during the period of interest. The correlation between the NEIO and URCS estimates both wheat and corn were relatively high, 0.7892 and 0.7133, respectively (Table 4.2). Soybean and barley estimates decline moderately between 1983-2000, and their graphs exhibit similar trends. For both commodities, the URCS estimate for marginal cost is extremely close to the NEIO estimate in the first two years (1996 and 1998) and then begins to grow further apart. Interestingly, the correlation calculated for barley, 0.7866, is much higher than that for soybeans, which is 0.6785. Wheat estimates also reveal the same sort of pattern between NEIO and URCS estimates as did soybeans and barley, but the difference in the estimated values is greater than with soybeans and barley. The marginal cost values for corn bear the greatest difference in values with respect to the NEIO and URCS approaches. It is interesting to note that for all four commodities, the difference between the NEIO and URCS estimates increase with time, although this differential varies by commodity.

---

[27] The data necessary for computation of the URCS cost estimates was available only for four years, 1996 and 1998-2000, and hence the MC line for URCS only contains four data points when evaluated at the mean value, whereas the NEIO estimates are available for all years in the study.

TABLE 4.2 CORRELATIONS BETWEEN OUR MC ESTIMATE AND URCS

Correlations between MC Estimates and URCS

Commodity	Correlation Value
Wheat	0.7892
Corn	0.7133
Soybeans	0.6785
Barley	0.7866
Chemicals	0.8415
Coal	0.7597

If the NEIO approach used in this paper and the URCS method yielded identical estimates for marginal cost, then plotting the estimated values against each other graphically would yield a 45-degree line. If however, the estimates differed from each other over time, as was implied for commodities in Figure 4.1, then this would be reflected by the position of the line generated by plotting NEIO and URCS estimates, relative to the 45-degree line on the same graph. Figures 4.2 and 4.3 contain this type of graph, which provide interesting insight for comparing the estimated values.

Figure 4.2 graphs the NEIO estimates versus the URCS estimates (with the 45-degree line) for the same four farm commodities represented in Figure 4.1. All commodities have a 45-degree line that lies above the NEIO/URCS line, indicating that for all four farm commodities the NEIO approach generated estimates greater than did the URCS approach. Estimates for wheat and soybeans display similarities in that the NEIO/URCS line continuously moves closer to 45-degree line, as marginal cost increases, thus inferring the estimates are closer to each other at higher costs per ton-mile. For barley, the NEIO/URCS line also moves closer to the 45-degree line at higher marginal costs, but begins to diverge at the end. As was implied from Figure 4.1, corn displays the largest differential between estimated values for marginal cost.

Figure 4.3 displays the same type of graphs as Figures 4.1 and 4.2, but does so for the other two commodities that were estimated using Equation 8, chemicals and coal. The distance between the 45-degree line and the NEIO/URCS line is much greater for these commodities than for the farm commodities described above. However, Table 4.2 indicates correlations for both commodities to be high, with that of coal being 0.7597 and the chemical correlation equal to 0.8415, the highest estimated correlation for any of the commodities. The position of the NEIO/URCS line below the 45 degree line suggests that for both coal and chemicals, the NEIO estimates exceed those of URCS. The marginal cost estimates for chemicals tend toward the 45-degree line most notably at the end of the NEIO/URCS line (shown by the sharp increase between the last two data points on the line). However, the opposite is true for coal, as the NEIO/URCS line runs parallel to the 45-degree line, except for a point diverging out toward the end.

Figure 4.1 **Estimates of Marginal Costs Over time (by commodity)**

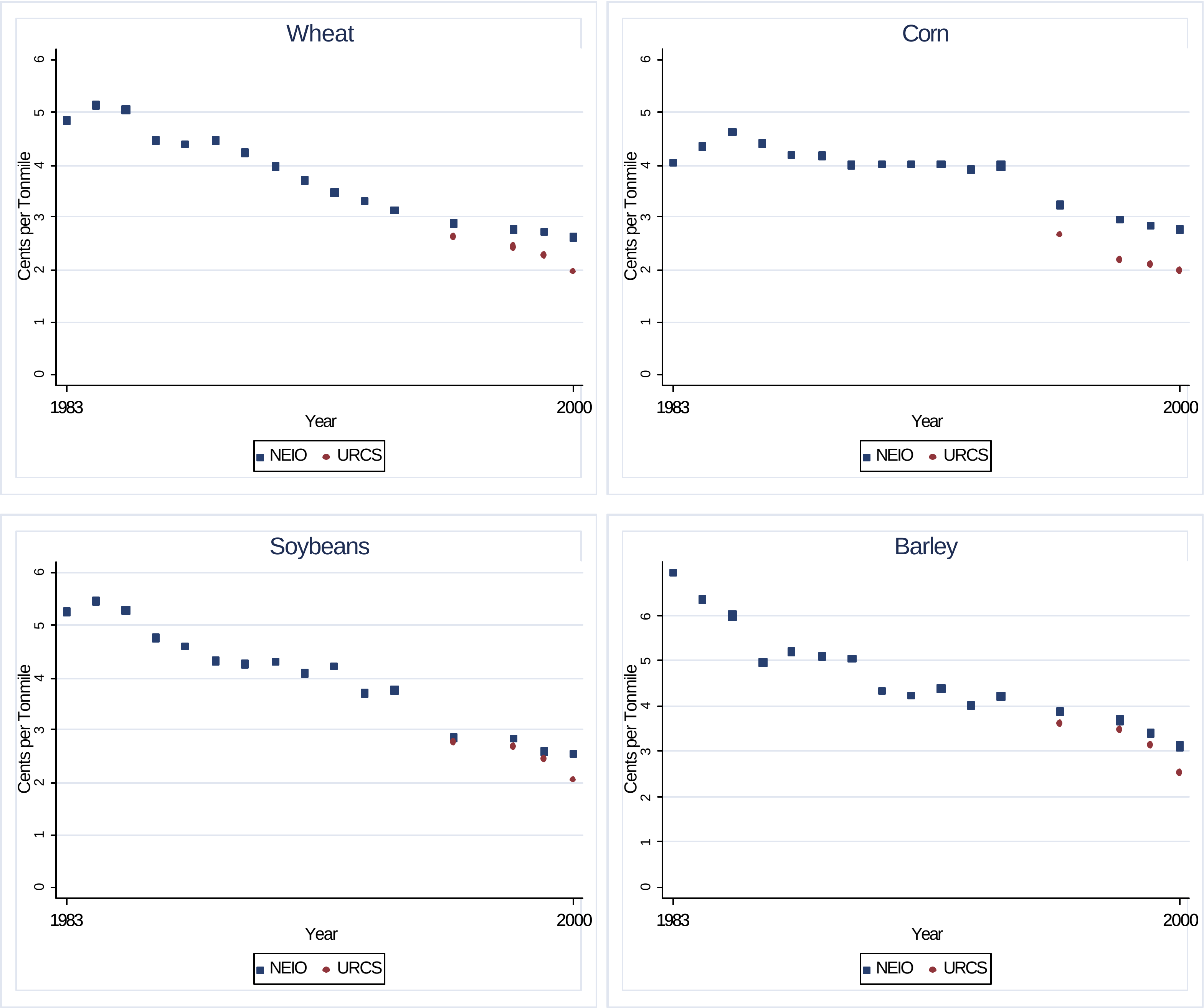


Figure 4.2 **Marginal Cost Comparisons by Commodity: NEIO Versus URCS**

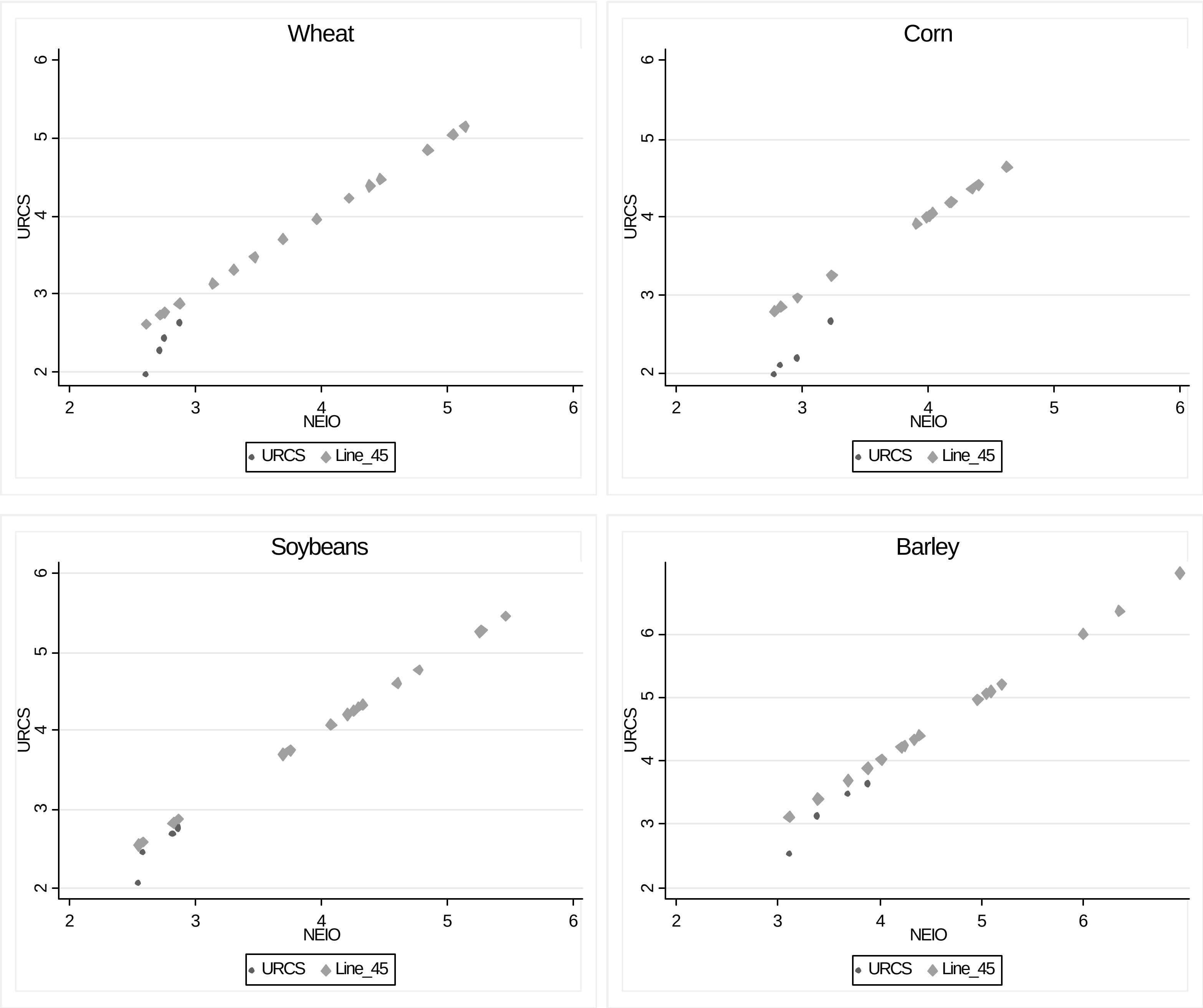
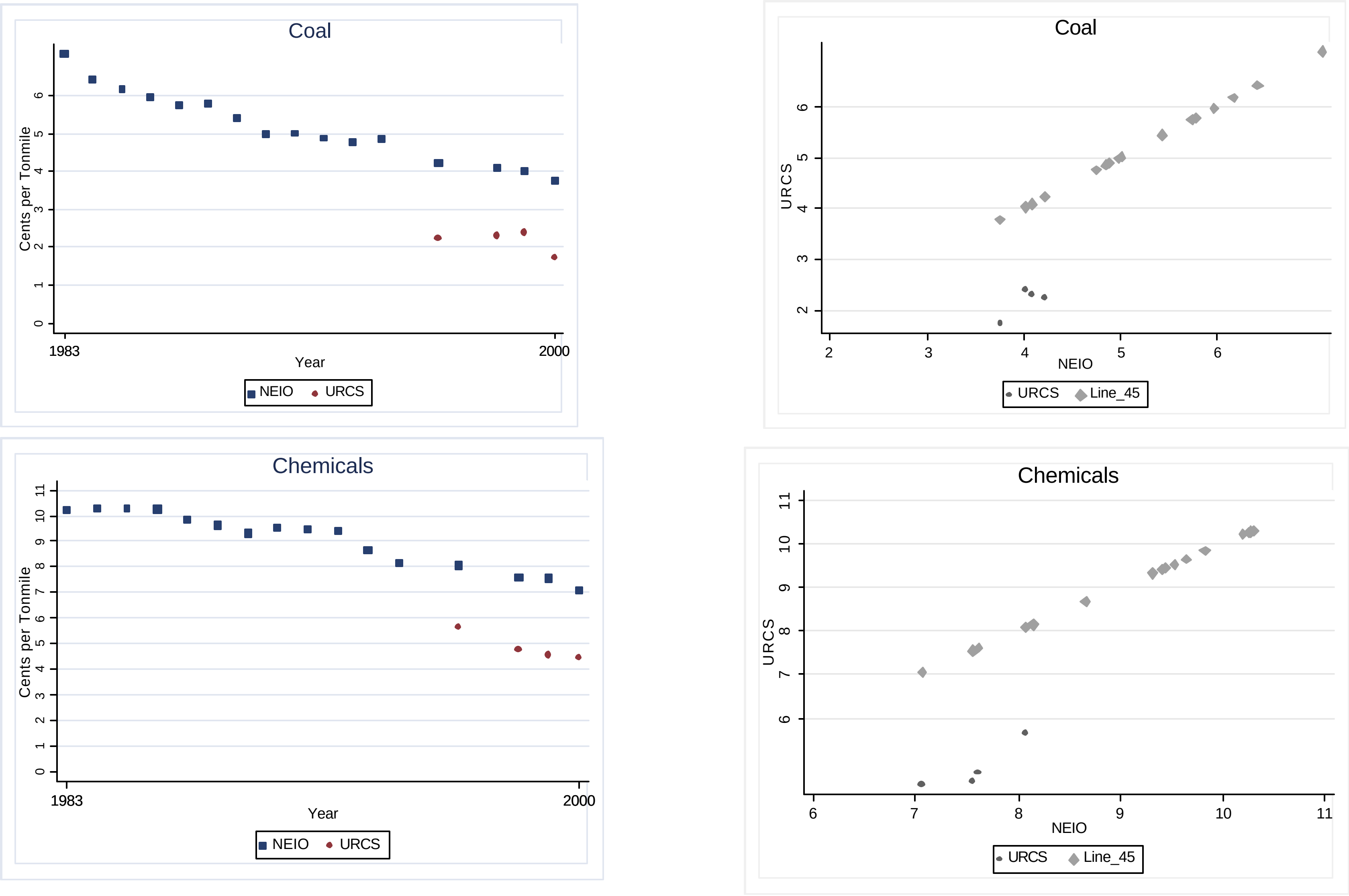


Figure 4.3 **NEIO and URCS Cost Comparison for Coal and Chemicals**



5. SUMMARY AND CONCLUSIONS

Determination of accurate railroad costs for a specific movement is extremely difficult due to the complexity of railroad networks, and production that occurs under economies of density and joint production over the networks. Railroads produce outputs delineated across many different dimensions including commodity, distance, shipment size, and a host of other attributes of firm, location, and shipment.

While the task of measuring movement-specific costs is difficult, it is necessary for railroads in their decisions on outputs, pricing, and investment, and for the STB in examining the reasonableness of rates in regulatory proceedings. The URCS and its predecessor RFA, attempt to simulate railroad individual movement costs through an activity costing approach, where the variability of separate activity expense equations is estimated based on an activity measure (e.g. train miles). These variability percentages are used to estimate movement-specific costs based on activities encompassed in a particular movement. However, as demonstrated, these efforts are not without fault.

Many of the theoretical advances introduced by economists are not encompassed in the regulatory approach to costing. Aggregate “econometric” cost functions fall directly from economic principles. But, the results of this report suggest such an approach does not appear to effectively estimate cost differences across individual movements. That is, system averages in such a context do not appear to capture the specificity needed to estimate movement-specific costs.

Because of limitations with the URCS approach and with the econometric aggregate cost function approach, this study examines a third approach titled “the New Industrial Organization Approach.” The NEIO approach uses disaggregate data on railroad rates to infer marginal costs of specific shipments. The NEIO marginal cost estimates simulated in this study show a strong correlation with URCS costs. While several refinements to the NEIO model may improve on results obtained, the result may provide another approach to rail costing, which relaxes a number of prior assumptions made in the regulatory approach to the costing of specific railroad movements.

6. REFERENCES

Association of American Railroads. Various Years. *Railroad Facts* Washington, DC: American Association of Railroads.

Azzam. A. 1997. "Measuring Market Power and Cost-Efficiency Effects of
Industrial Concentration" *Journal of Industrial Economics* (34:377-386)

Barbera, A., C. M. Grimm, K. A. Phillips, and L. J. Selzer. 1987. "Railroad Cost Structure-Revisited." *Journal of the Transportation Research Forum*. 28(1): 237-44.

Barnekov, C.C. and Kleit, N. 1990. "The Efficiency Effects of Railroad Deregulation in the United States." *International Journal of Transport Economics* 17: 21-36.

Baumol, Panzer and Willig. 1982. *Contestable Markets and the Theory of Industry Structure* (New York: Harcourt, Brace Jovanovich).

Bereskin, Gregory C. 1989. "An Econometric Alternative to URCS (Uniform Railroad Costing System)." *The Logistics and Transportation Review* 25(2): 99-128.

Bereskin, Gregory C. "Estimating Maintenance-of-Way Costs for U.S. Railroads After Deregulation." Transportation Research Record 1707, Paper No. 00-1109, St. Ambrose University, Dept. of Economics and Business: 13-21.

Bereskin, Gregory C., "Econometric Estimation of Costs for Specific Railroad Freight." Mimeo.

Berndt, Friedlaender, Chiang and Vellturo (1993)

Berndt, Ernst R., A. F. Friedlaender, J. S. W Chiang, M. Showalter, and C. A. Vellturo. 1993. "Cost Effects of Mergers and Deregulation in the U.S. Railroad Industry." *Journal of Productivity Analysis* 4(1-2): 127-44.

Bitzan, John D. 1999. "The Structure of Railroad Costs and the Benefits/Costs of Mergers." *Research in Transportation Economics* 5: 1-52.

Bitzan, John D. and Theodore E. Keeler (forthcoming). "Productivity Growth and Some of its Determinants in the Deregulated U.S. Railroad Industry." *Southern Economic Journal* 70(2): 15-36.

Borts, G. 1960. "The Estimation of Rail Cost Functions." *Econometrica.* 28:108-31.

Boyer, Kenneth D. 1977. "Minimum Rate Regulation, Modal Split Sensitivities, and the Railroad Problem." *Journal of Political Economy* 85: 493-512.

Boyer, Kenneth D. 1981. "Equalizing Discrimination and Cartel Pricing in Transport Rate Regulation." *Journal of Political Economy* 89: 270-286.

Boyer, Kenneth D. 1987. “The Cost of Price Regulation: Lessons from Railroad Deregulation.” *Rand Journal of Economics* 18: 408-416.

Bresnahan. Timothy F. 1989. “Empirical Studies of Industries with Market Power.” *Handbook of Industrial Organization Vol. II*, edited by R. Schamalensee and R. D. Willig (Amsterdam: North Holland), 1011-1058.

Brauetigam, R. R., A. F. Daughety, and M. A. Turnquist. 1984. “A Firm Specific Analysis of Economies of Density in the Railroad Industry.” *The Journal of Industrial Economics*. 33(1): 3-20.

Brown, R. S., D. W. Caves, and L. R. Christensen. 1979. “Modelling the Structure of Cost and Production for Multiproduct Firms.” *Southern Economic Journal*. 46(1): 256-73.

Burton, Mark L. 1993. “Railroad Deregulation, Carrier Behavior, and Shipper Response: A Disaggregated Analysis.” *Journal of Regulatory Economics* 5: 417-34.

Caves, Douglas W., Christensen, Laurits R., and Swanson, Joseph A. 1980. “Productivity in the US Railroads, 1955-74.” *Bell Journal of Economics* 11: 166-81.

Caves, Douglas W., Christensen, Laurits R., and Swanson, Joseph A. 1981. “Productivity Growth, Scale Economies, and Capacity Utilization in the U.S. Railroads, 1955-1974.

Caves, D. W., L. R. Christensen, and M. W. Trethaway. 1980. “Flexible Cost Functions for Multiproduct Firms.” *Review of Economics and Statistics*. 62(3): 477-81.

Caves, Douglas W., Christensen, Laurits R., Trethaway, M.W., and Windle, R.J. 1985. “Network Effects and the Measurement of Returns to Scale and Density for U.S. Railroads.” In *Analytical Studies in Transport Economics*, edited by A.F. Daugherty. New York: Cambridge University Press.

Christensen, D. W., L. R. Jorgenson, and L. Lau. 1973. “Transcendental Logarithmic Production Functions.” *Review of Economics and Statistics*. 55(1): 28-45.

Chiang; S. Judy Wang and Ann F. Friedlaender, 1984. Output Aggregation, Network Effects and the Measurement of Trucking Technology. *The Review of Economics and Statistics* (66(2): 267-76.

Chiang; S. Judy Wang and Ann F. Friedlaender, 1985. Truck Technology and Efficient Market Structure. The Review of Economics and Statistics 67(2): 250-258.

Clark, J. M. 1923. *Studies in the Economics of Overhead Costs* (Chicago, University of Chicago Press).

Friedlaender, Ann F., and Spady, Richard H. 1981. *Freight Transportation Regulation: Equity, Efficiency, and Competition in the Rail and Truck Industries.* Cambridge, MA: MIT Press.

Friedlaender, Ann F., E. R. Berndt, J. S. W. Chaing, M. Showalter, and C. A. Vellturo. 1993. “Rail Costs and Capital Adjustments in a Quasi-regulated Environment.” *Journal of Transport Economics and Policy* 27(2): 131-52.

Harris, R. G. 1977. “Economies of Density in the Railroad Freight Industry.” *Bell Journal of Economics*. 8(2): 556-64.

Interstate Commerce Commission. 1982. “The Uniform Railroad Costing System, 1980 Railroad Cost Study.” Washington, D.C.: Interstate Commerce Commission, Bureau of Accounts.

Irwin, Douglas A., and Peter J. Klenow. 1993. “Learning-by-Doing Spillovers in the Semi-Conductor Industry.” *The Journal of Political Economy* 102(6):1200-27.

Ivaldi, M. and McCullough, G.J. 2001. “Density and Integration on Class I U.S. Freight Railroads.” *Journal of Regulatory Economics* 19(2): 161-182.

Keeler, Theodore E. 1974. “Railroad Costs, Returns to Scale and Excess Capacity.” *Review of Economics and Statistics* 56(2): 201-208.

Lorenz, M. O. 1916. “Cost and Value of Service in the Railroad Rate-Marking.” *Quarterly Journal of Economics*. XXX: 205-32.

MacDonald, James M. 1987. “Competition and Rail Rates for the Shipment of Corn, Soybeans, and Wheat.” *Rand Journal of Economics* 18(1):151-163.

MacDonald, James M. 1989. “Railroad Deregulation, Innovation, and Competition: Effects of the Staggers Act on Grain Transportation.” *Journal of Law and Economics* 32: 63-96.

MacDonald, James M. and Cavalluzzo, Linda C. 1996. “Railroad Deregulation: Pricing Reforms, Shipper Responses, and the Effects on Labor.” *Industrial Labor Relations Review* 50: 80-91.

McBride, Mark E. 1983. “An Evaluation of Various Methods of Estimating Railway Costs.” *The Logistics and Transportation Review* 19(1): 45-66.

McFarland, H. 1989. “The Effects of United States Railroad Deregulation on Shippers, Labor, and Capital.” *Journal of Regulatory Economics* 1: 259-70.

Meyer, J. R. 1958. “Statistical Cost Functions: Some Methodological Aspects as Illustrated by the Determination of Rail Passenger Costs.” *American Economic Review*. 48(2): 209-222.

Meyer, John R., Peck, Merton J., Stenason, John R., and Zwick, Charles. 1959. *The Economics of Competition in the Transportation Industries.* Harvard University Press.

Railroad Accounting Principles Board. 1987. “Railroad Accounting Principles; Final Report.” Volume 2.

Rhodes, George F. Jr. and M. Daniel Westbrook. 1986. “Econometric Analysis of Costing System Components in Rail Rate Regulation.” *Journal of Business & Economic Statistics* 4(3): 289-303.

Rosse, James. 1970. "Estimating Cost Function Parameters Without Using Cost Data: Illustrated Methology." *Econometrica*. 38:256-75.

Spady, Richard. 1985. "Using Indexed Quadratic Cost Functions to Model Network Technologies," in *Analytical Studies of Transport Economics* edited by Andrew Daughety (Cambridge: Cambridge University Press).

Spady, Richard H., and Ann F. Friedlaender, "Hedonic Cost Functions for the Regulated Trucking Industry," *The Bell Journal of Economics*. 9(1):159-79.

Tolliver, Denver D. 1984. "Economies in Density in Railroad Cost Finding: Applications to Rail Form A." *Logistics and Transportation Review* 20(1): 3-24.

Waters II, W. G. II and A. D. Woodland. 1984. "Econometric Analysis and Railway Costing." The Centre for Transportation Studies, University of British Columbia, North Oxford Academic Publishing Co.: 1-101.

Westbrook, Daniel M. 1988. "Research Report on URCS Regression Equations." Interstate Commerce Commission, Bureau of Accounts.

Wilson. 1985. "Network Effects and Entry Regulation in US Trucking." Mimeo.

Wilson, Wesley W. 1994. "Market-Specific Effects of Rail Deregulation." *Journal of Industrial Economics* 42: 1-22.

Wilson, Wesley W. 1996. "Legislated Market Dominance." *Research in Transportation Economics* 4(1): 33-48.

Wilson, Wesley W. 1997. "Cost Savings and Productivity Gains in the Railroad Industry." *Journal of Regulatory Economics* 11: 21-40.

Winston, Clifford. 1985. "Conceptual Developments in the Economics of Transportation: An Interpretive Survey." *Journal of Economic Literature* 23(1): 57-94.

Winston, Clifford. 1993. "Economic Deregulation: Days of Reckoning for Microeconomists." *Journal of Economic Literature* 31(9): 1263-90.

Winston, Clifford, Corsi, T.M., Grimm, Curtis M., and Evans, C.A. 1990. *The Economic Effects of Surface Freight Deregulation.* Washington, D.C.: The Brookings Institute.

Wolfe. K. E. 1986. "The Carload Waybill Statistics: A Content Analysis." *Proceedings of the Transportation Research Forum*. 27:244-252.

Wolfe. K. E. 1991. "The Interstate Commerce Commission's Public Use Waybill File: Concern for Misinterpretations." *Journal of the Transportation Research Forum*. 32(263-265.

Appendix A. Econometric Models of Cost

Over the past 40 years, several studies have estimated aggregate railroad cost functions. In fact, the first aggregate railroad cost functions were estimated in the late 1950s (Meyer 1958), but until the middle 1970s most cost function estimations were ad hoc and/or specified as linear functions.

Keeler (1974) pointed out problems present in most of the early cost studies — either they estimated total costs as a function of output without including a measure of capacity or they estimated total costs as a linear function of output and track mileage. Keeler was critical of the first approach because it assumed that railroads had adjusted to long-run equilibrium – an assumption that was incorrect given institutional constraints placed on the rail industry prior to deregulation. This problem previously was illuminated by Borts (1960), who referred to the bias present when firms are assumed to be on their long run cost curve, but have systematic deviations from planned output as regression fallacy. The second approach assumed that factor proportions between track and other inputs were fixed. Keeler argued that such a model was not appropriate and that marginal maintenance and operating costs should rise as the railroad plant is used more intensively. To remedy these problems, Keeler formulated a short-run cost function from neoclassical economic theory using a Cobb-Douglas production function. One important contribution of Keeler's study was that he distinguished between two different types of scale economies in the rail industry – each with markedly different implications for the behavior of railroad costs and policies aimed at railroad efficiency. Economies of density result when average costs decrease with increases in traffic density over a fixed system. Economies of size result when average costs decrease with increases in the size of the network.

Another important contribution of Keeler's study was the method he used to obtain a long-run cost function. He estimated a short-run cost function because most railroads were operating at excess capacity, and then derived the optimal capital stock and plugged it into the short-run cost function to get the long-run cost function. This approach merely follows the text book microeconomic derivation of the long-run cost function, but nonetheless made a significant contribution to the estimation of railroad cost functions. He found substantial returns to traffic density, constant long-run returns to scale, and substantial excess capacity for all railroads studied.

The next landmark study in rail cost analysis was done by Harris (1977), who studied economies of density in railroad freight services. Harris pointed to several problems in previous rail cost studies, including: (1) continued confusion between economies of density and size, despite the paper by Keeler; (2) use of inappropriate measures of output and capacity; previous studies used gross ton-miles for output, which include empty mileage and equipment weight, and miles of track for capacity, which includes duplicate track over the same route; (3) inadequate division of costs between passenger and freight services, which biased against finding economies of density; (4) no clear rationale behind regional stratification; (5) failure to include important variables, such as average length of haul, resulting in biased coefficient estimates; and (6) failure to include return on capital investment in costs. The author originally explained total rail costs with revenue ton-miles, revenue freight-tons, and miles of road. Because of heteroskedasticity due to a larger error term with larger firm size, he divided the entire equation by revenue ton-miles. This is equivalent to estimating average rail costs for freight services with the reciprocals of average length of haul and traffic density. Harris found significant economies of traffic density for rail freight services, and through the estimation of several cost accounts with the same formulation, he found there was a significant increase in density economies when return on capital investment costs were included, that fixed operating costs accounted for a significant portion of economies of density, and that maintenance of way and transportation expense categories combined to account for more than 50 percent of economies of density. Harris' study made a large contribution to the study of rail costs by showing biases caused by several flaws in previous rail cost studies and by showing a need to consider data measurement and specification issues when estimating rail cost functions.

A major breakthrough in railroad cost analysis took place with introduction of the transcendental logarithmic (translog) function by Christensen, Jorgenson, and Lau (1973). The translog function has a basic advantage over other functional forms in estimating costs – it is flexible and does not place heavy restrictions on production structure that other functional forms do. In fact, the translog function can be thought of as a second order approximation to an arbitrary function.

The first study to use the translog function to examine railroad cost structure was performed by Brown, Caves, and Christensen (1979). In examining benefits of the translog cost function over previous functional forms, they estimated a long-run railroad cost function with the unrestricted translog cost function (linear homogeneity of factor prices was the only restriction imposed), one with separability in outputs imposed, and one with homogeneity in outputs imposed. The authors found the translog cost function to be a significant generalization of the other two models. In examining long-run returns to scale, they found significant multiproduct scale economies for 66 out of the 67 railroads in the sample. Moreover, significant errors in estimating marginal costs and scale economies were present when using the restricted models.

The next major contribution to the study of railroad costs was contained in a book by Friedlaender and Spady (1981) which examined the potential impacts of railroad and trucking deregulation. The authors estimated a short-run variable cost function for railroads, making several innovations to the translog cost function. Innovations in their estimation procedure included: (1) distinguishing between way and structures capital and route mileage (route mileage represents increased carrier obligation, while way and structures capital are a factor of production); (2) including the percentage of ton-miles that are due to the shipment of manufactured products as a technological variable (accounts for differences in costs associated with different types of traffic); and (3) distinguishing between high and low density route miles. Because they distinguished between way and structures capital and route miles, the authors were able to measure short-run returns to density (holding way and structures capital fixed) and long-run returns to density (allowing way and structures capital to vary, but holding route miles fixed). They found long-run increasing returns to density, but decreasing returns to firm size. Friedlaender and Spady's study made a contribution by making major improvements in the railroad cost function, many of which have not been repeated in more recent studies.[28]

One problem present in early railroad cost studies using the translog function was the existence of zero passenger output for some railroads. Since the translog cost function is in logarithms, zero values for output can not be included in the estimation. Because of this problem, early translog rail cost studies eliminated all observations for railroads that did not provide passenger service. However, Caves, Christensen, and Tretheway (1980) came up with a solution to this problem by proposing a generalized translog multiproduct

---

[28] More recently, papers by Berndt, Friedlaender, Chiang, & Vellturo (1993), and Friedlaender, Berndt, Chiang, Showalter, and Vellturo (1993) have included similar innovations of distinguishing route miles from way and structures capital, and including the percentages of output due to various types of commodities. Using 1974-1986 data, these studies have shown increasing returns to density and slightly increasing returns to firm size.

cost function. The generalized translog cost function differs from the translog cost function in that it uses the Box-Cox Metric for outputs, rather than just the log of outputs. The authors also evaluated the generalized translog cost function and three other cost functions using three criteria, including: (1) whether it met linear homogeneity in input prices for all possible price and output levels, (2) the number of parameters that had to be estimated, and (3) whether it permitted a value of zero for one or more outputs. The quadratic, translog, and combination of Leontif cost function with a generalized linear production function all had problems with one or more of these criteria, while the generalized translog cost function did not. When testing the generalized translog cost function against the translog cost function using railroad cost data, the authors found significant differences resulting from using the full sample instead of only those with non-zero outputs for passenger and freight output.

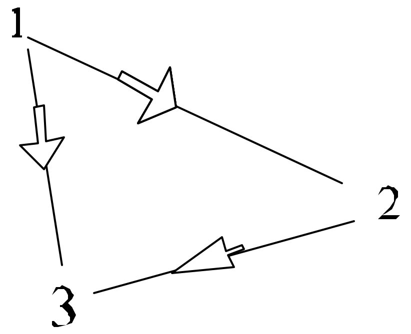
At the same time as other innovations in the translog cost function were taking place, two studies aimed at measuring changes in railroad total factor productivity over time also made use of the translog cost function (Caves, Christensen, and Swanson 1980 and 1981). Caves, Christensen, and Swanson showed that using a flexible production structure resulted in a much different estimate of productivity growth than previous studies that used index procedures to measure productivity growth, implicitly imposing several restrictive assumptions, such as constant returns to scale and separability of outputs and inputs. Their cost estimations included a short-run variable cost function that held way and structures capital fixed, and a long-run total cost function. Both models showed slightly increasing long-run returns to scale when increased ton-miles and passenger miles were assumed to result solely from increases in length of haul, but showed constant returns to scale when increased ton-miles and passenger miles were assumed to result solely from increases in tonnage and passengers. The models could not distinguish between returns to density and returns to size, but nonetheless provided another estimate of overall returns to scale.

Brauetigam, Daughety, and Turnquist (1984) brought attention to a problem that was present in many previous railroad cost estimations. They showed that because there are many basic differences between railroad firms, estimation of a cost function that fails to consider firm effects can lead to biases in the coefficients of important policy variables. The authors estimated a railroad cost function using time-series data for an individual firm, in an attempt to highlight biases in studies using cross-sectional or panel data. In addition to focusing attention on the possible biases from failure to consider firm effects in a cost function estimation, their study also provided two other useful innovations to the estimation of railroad costs. First, they included speed of service as a proxy for service quality and found that its omission resulted in an understatement of economies of density. Second, they included a measure of "effective track," which considered mileage and the amount invested in existing track above that required to offset normal depreciation. This essentially was equivalent to the innovation employed by Friedlaender and Spady (1981), which included track mileage and way and structures capital. Finally, the authors found significant economies of density for the railroad studied.

Another study that brought attention to the importance of considering firm effects in estimating returns to density was a study by Caves, Christensen, Tretheway, and Windle (1985). The authors estimated long-run cost function using 1951 through 1975 data, finding substantial increasing returns to density and slightly increasing or constant returns to overall scale. Like Friedlaender and Spady, they distinguished route miles from way and structures capital, as they included a capital price and a route miles variable. The study made significant contributions in highlighting the bias that may occur from estimating returns to density without considering firm effects, and in precisely defining measures of returns to density and scale.

All of the previously mentioned studies used data prior to railroad deregulation. Since the study by Caves et. al there has been an assortment of studies using post deregulation data.

Barbera, Grimm, Phillips, and Selzer (1987) estimated a translog cost function for the railroad industry using data from 1979 through 1983. The study made improvements over some previous studies in its measurement of capital expenses, as it used the replacement cost of capital rather than book values in calculating return on investment costs, and by using depreciation accounting techniques rather than the railroad convention of betterment accounting.[29] The study found significant increasing returns to density for rail freight services, but constant overall returns to scale. It highlighted the importance of including the current replacement cost of capital in cost estimates.



Wilson (1997) estimated a short-run variable cost function in revisiting the measurement of total factor productivity in the post-deregulation era. The study used more recent data (1978-1994), while maintaining some innovations used in the studies using pre-deregulation data such as using high density and low density miles of track, speed to measure the quality of capital, and the percent of shipments that were made by unit trains. The study also added several other innovations by including variables such as the percent of traffic interlined with other carriers, high density and low density gross ton miles, and firm specific dummy variables meant to measure the effects discussed by Braeutigam, et. al.

Ivaldi and McCullough (1999) examined economies of density in the Class I railroad industry using a cost function that differentiated between car miles of bulk traffic, high value equipment, and other equipment. In addition to examining economies of density, the study also examined vertical relationships between freight operations and infrastructure. The study found substantial returns to density and cost complementarities between different outputs, suggesting that "open access" could lead to increased costs. Moreover, it found anticomplementarities between output and infrastructure, suggesting potential coordination problems if railroad operations and infrastructure were separated. The study made a significant contribution by more closely capturing the multi-product nature of railroads, and by including methods to measure output-infrastructure cost relationships. However, one potential problem with the study was in its use of car miles, as car miles do not necessarily represent the output of railroad firms.

Bitzan (1999) estimated a multiproduct translog cost function to examine cost subadditivity in the railroad industry. The study was unique in its inclusion of three distinct railroad outputs - unit train ton-miles, through train ton-miles, and way train ton-miles. The study found subadditivity over a fixed network size, but not as networks are expanded.

---

[29] However, studies by Friedlaender and Spady (1981), Caves, Christensen, and Swanson, (1980, 1981) and others make similar improvements.

Appendix B. New Empirical Industrial Organization

The New Empirical Industrial Organization (NEIO) model is a standard empirical framework in industrial organization, which has been used to estimate marginal costs and markups in particular industries. Of particular use to this study is the possibility of using such an approach to estimate marginal costs of a specific movement.

As noted in the classic work by Bresnahan (1989), “A typical NEIO paper is first and foremost an econometric model of an industry.” In the most complete form, such a model takes the form:

$$InverseDemand: \qquad P = P(Q, X^{D}; b^{D});$$

$$Costs: \qquad C_i = C_i(Q_i, X^{C}; b^{C});\ and$$

$$\Pr icing: \qquad P = MC^{i}(Q_i, X^{C}, b^{MC}) - \frac{\partial P(Q, X^{D}; b^{D})}{\partial Q_i} q\,.$$

In this system of equations, demand and costs are self evident. The pricing relation is, however, emanates from the standard marginal revenue = marginal cost condition of profit maximization. In this model, prices (P), quantities (Q, Q_i), costs (C), demand shifters (X^D), cost shifters (X^C) form the observables through which the parameters (β^D, β^C, β^{MC}, and θ) are estimated.

Of particular interest to the present study is the notion that through prices, conditions of costs can be estimated. We begin with a simple illustration of the usefulness of this approach to the problem at hand (i.e., the costing of individual railroad movements), where we assume competitive behavior. With competitive pricing, the second term of the pricing relation is zero, and prices are equal to marginal costs. Under this assumption, the marginal cost parameters can be estimated with data on prices, outputs, and other cost shifters. That is, the pricing relation becomes:

$$P = MC^{i}(Q_i, X^{C}; b^{MC})$$

This is an extremely powerful model from which costs function parameters can be estimated through observations on rates and movement characteristics.

More generally, rail rates may not be competitive. They may be in excess of marginal costs. In such cases, the same procedure may be used, however it is more complicated. Specifically, the econometrician now must specify not only the cost function, but also the markup term (the second term of the pricing relation). There are many possibilities. We illustrate an approach taken by Irwin and Klenow in their 1993 *Journal of Political Economy* paper examining the effects of learning by doing in the Data Random Access Memory

(DRAM) market.[30] In this model, they assumed that firms competed in a Cournot fashion (i.e., in equilibrium, firm maximize profit by choosing output given their rivals outputs, and all firms do so simultaneously). In such a case, the pricing relation can be written as

$$\frac{P-MC}{P}=-\frac{s_i}{e_D}$$

where s_i is firm i's market share and e_D is the elasticity of demand. In their study, they assumed a demand elasticity and observed prices and market shares. By solving this equation then they could construct a measure of marginal costs as

$$MC=P\left(1+\frac{s_i}{e_D}\right)$$

They then used this measure with a set of explanatory variables to estimate the effects of learning in DRAM markets.

These two models form the basis for our empirical work in Section 4 with a few non-trivial modifications. In particular, we do not assume that prices are the result of a Cournot game, and we do not assume elasticities. Rather, we frame our model around a separation of cost variables and markup variables. We then estimate markups and marginal costs in a single equation and back out estimate of marginal costs from the estimated results. The advantage of this approach is that marginal costs can be estimated using data currently available for specific movements (i.e., the waybill sample). This approach is in stark contrast to either URCS or the econometric approach to railroad costing wherein system aggregates of costs and/or cost components are then used along with explicit and implicit assumptions to form disaggregate measures of individual movement costs. We provide a more detailed explanation of our approach in Section 4. For the remainder of this section, we summarize some of the studies that have used this approach to examine the level and determinants of railroad rates to examine intermodal competition and the effects of partial deregulation. These studies form the basis for our decomposition of cost and markup variables used later.

The studies that we use to frame our application of the NEIO to railroad costing all use a price (rate) dependent equation, which can be interpreted using an NEIO frame of reference. Essentially, these previous studies use a model of rates, which apply to shippers of various commodities, to examine the effects of such items as partial deregulation, consolidation, technological advancements, geographic and commodity-specific differences, and inter/intramodal competition. The empirical methods and/or data varies substantially across studies with early studies based on aggregate data, and more recent studies using more disaggregate data. In all the studies, models estimated and results can be represented and interpreted as using an NEIO framework. In the remainder of this section we provide a brief synopsis of this literature and the types of questions addressed in the studies. We do note here, however, that specification of costs is secondary in all

---

[30] Learning-by-doing is the notion that firms learn their experience. Learning reduces costs. The typical empirical representation of learning in this model is with cumulative production levels – the quantity a firm has produced up to the time observed.

of these papers. That is, rates form a dependent variable to be explained by a set of variables including both cost and markup variables. In all cases, cost specification is of secondary import to the markup specification.

A prevalent topic in previous literature regarding rail rates has centered on the discussion of deregulation in the US railroad industry. Specifically, many early studies sought to identify the effects of the Staggers Rail Act of 1980 (which implemented industry deregulation and increased rail carriers' freedom in choosing rates to charge shippers for hauling various commodities) on rail rates. Literature covering this type of rate analysis yielded mixed results concerning how the Staggers Act had impacted rail rates.

Boyer (1987) explores the difference between rate levels and railroad market shares after deregulation, with those rates and shares that might have occurred in the absence of deregulation. Using OLS, Boyer estimates the effect of deregulation and train weight on the dependent variable, average revenue per ton mile (ARTMR), which reflects rate. From this estimation it is inferred that train weight explains 90 percent of the variance in ARTMR, while deregulation likely has increased rates by 2 percent. Coinciding with these results, Boyer also estimates the difference in market shares (by the same method) and found that in 1983, three years after partial deregulation had occurred in the industry, railroads were losing market share, about .48 percent per year.

Barnekov and Kleit (1990), however, generate results opposite that of Boyer. They attribute differences in conclusions between the two studies to problems with the approach used by Boyer, which they identify as including improper specification of the rate model (specifically, improper specification of the dummy variable and not recognizing that changes in train weight itself was a result of deregulation), failure to examine larger impacts of deregulation on costs and service levels, and the exclusion of any demand side variables. Barnekov and Kleit re-estimate Boyer's model, specifying the deregulation dummy variable to begin in 1981 and extending the data from 1985 to 1987. In doing so, a Durbin-Watson statistic of 0.7 indicates omitted variable bias from the Boyer specification. In light of this finding, Barnekow and Kleit expand the data set to include data from 1970-1987 and add some key variables to their reduce-form specification for rail rates. The additional variable included a ratio of the number of rail contracts filed each year, the percent change in GNP (a demand factor variable), and variables representing bulk commodities and average length of haul.[31] Results from their estimation indicated that the Staggers Act reduced rates by 18.5 percent by 1987. They also concluded that bulk commodities and average length of haul negatively effected rates, while truck rates showed a positive relationship with rail rates, indicating competition. In sum, the study by Barnekov and Kleit asserted that deregulation saved shippers billions of dollars through decreased rates.

Building off earlier models created by Boyer (1987) and Barnekov and Kleit (1988), McFarland (1989) utilized additional data (spanning 1969-1987) and an approach similar to those previously described to study to examine the effects of deregulation on shipper rates, labor, and capital. McFarland adds density as an explanatory variable in his equation, with a deregulation dummy variable (DR) identical to that used by Boyer and a time/deregulation dummy variable (TR) parallel to that used by Barnekov and Kleit. Consequently, his

---

[31] The ratio of the number of contracts filed each year was defined as the number of contracts each pear, divided by the number of contracts that were filed in 1987. This variable was included as the authors believed "contract provision" to be the single most important aspect of the Staggers Act. The contract provision essentially provided total confidentially of terms and rates, and such contracts were exempt from regulatory review. Hence, a dramatic increase in the number of contracts filed occurred following the passage of the act.

study produced mixed results. On one hand, interpretation of MacFarland's empirical estimates allege that deregulation increased rates (as the estimated coefficient for DR displayed a positive sign), but that deregulation also decreases rates by increasing the pace of technology (denoted by the negative coefficient of TR). As a result, McFarland speculates that some shippers enjoyed an increase in service quality without higher rates, while other shippers did experience rate increases.

Considering the diverse conclusions drawn from the preceding studies of deregulation and rail rates, the demand for further analysis of the topic emerged. Recognizing the possibility of biased results from earlier studies, due to the use of aggregate data in estimating deregulation effects, MacDonald (1987) turned to examine rate competition among railroads by investigating pricing behavior since deregulation. Using data on corn, soybeans, and wheat from the 1983 ICC Annual Waybill Sample, MacDonald performs an analysis of rates, aiming to specify reasonable measures of marginal cost (MC) and competitive conditions. A survey of these narrowly defined commodities was chosen so that changes in rates would reflect differences in shipment characteristics and competition only (MacDonald 1987).

MacDonald defines the ratemaking process (the rate) as a function of MC and the elasticity of demand facing an individual firm. Thus, the final equation for estimation relates rates to determinants of MC (distance, tonnage, and volume of the shipment), and competition (from barge and railroad). The data used in the estimation are disaggregated by location and the estimation was done for each commodity, separately.[32] MacDonald found tons, miles, and volume, which represent determinants of MC, to be negatively related to rates for all three commodities. The variable used to measure railroad competition was specified as 1/herfindahl index, and displayed a negative coefficient estimate indicating that increased competition causes lower rates. This study also revealed that rates tend to increase as barge competition becomes more remote.

MacDonald (1989) implements a similar study to that described above in which the focus specifically is centered on the effect of rail deregulation on grain transportation. In this latter study, MacDonald explores the possibility of geographic variations in effects of rail deregulation, hypothesizing that if the Staggers Act was successful in promoting intermodal competition, that this effect would be most prominently reflected in the Great Plains (where wheat production is concentrated). Using ICC Waybill data from 1981-1985 and a nearly identical regression specification from his previous study (except for the inclusion of a new variable, tons per car), MacDonald reports the same relationships for the MC, size, and competition variables as mentioned formerly. However, he extends the analysis (from the previous paper) and separately estimates regional differences in rate trends. From this, the results reveal that the Great Plain states exhibit an overall declining pattern in rates, and hence it could be conferred that the Staggers Act was successful in introducing interrail competition in this area.

Using the public version of the ICC Waybill data from 1973-1987, Burton (1993) follows the trend of the literature in choosing to analyze the relationship between rail rates and deregulation. However, Burton includes in his study a model of shipper response, thus yielding an innovative approach to studying the topic. Burton specifies a demand and cost equation for rail services, which he combines to define a profit equation. Assuming that railroads are profit-maximizing firms, the profit equation is optimized to obtain the profit-maximizing rate for rail service. This rate then is regressed with the same explanatory variables used by

---

[32] The data being disaggregated by location simply means that the data are individual observations of shipments from specific origin points.

MacDonald (1987) and a measure of intramodal competition, DIRSRV, (defined as the number of carriers offering service between the specific origin-destination pair).
Each variable in the equation was coupled with the deregulation dummy variable to form interaction variables. The estimated coefficients from the regression reveal that the recently set rates were more sensitive to the rates of competing carriers, than were the rates that had been set before deregulation. Coinciding with previous studies, the availability of water transport was estimated to negatively impact rates, as was the shipment size variable, tons. While increased interchanges were deemed to be of increased importance post-deregulation, the variable miles (miles of the shipment) exhibited itself as the strongest predictor of rates. These results generally coincide with those discovered by MacDonald, but Burton broadens his study in an interesting way.

An estimate of rates is generated that reflects what rates might have been if the Staggers Act had not been implemented. These rates then are compared with that of the previous regression, rendering evidence that although all rates decrease because of deregulation, rates for high-value commodities decreased 3-4 times faster than the rates charged for bulk commodities, due to deregulation. Furthermore, examining the theory that shippers change characteristics of shipments to realize rate savings, Burton reports findings that increased rail traffic occurred in areas with higher rail competition. This lends support of the hypothesis that shippers did indeed respond to changes in the structure of rates, as Staggers seems to have lead these shippers to use rail service when alternate modes were available.

For the most part, the former literature has concentrated on the following question: How did the passage of the Staggers Act affect rail rates for shippers? In essence, the literature focused on identifying the increase or decrease of rates since deregulation. However, Wilson (1994) uses the new NEIO approach to assess a different area of this topic. In his analysis of the market specific effects of rail deregulation, Wilson determines if deregulation is the *reason* for the lower rail rates. The empirical analysis conducted is done so for 34 different commodity classifications, which vary heavily in terms of demand and cost characteristics. Utilizing the aforementioned NEIO approach, Wilson develops a model that includes estimates of markups over marginal costs, (an indication of the exercise of market power). Hence, in theory, rates will increase (decrease) under deregulation only if the increases in markups above marginal cost outweigh (are less than) the cost savings.

The analysis performed in the preceding study by Wilson includes an estimated model of rates for the 34 different commodity groups, by which the effects of deregulation are allowed to vary.[33] The data used in the study were from the ICC Waybill, but span a 16-year period from 1972-1988. For the 34 commodities, specific rates, average length of haul, load, and density are calculated and used. Results show that changes in rates from deregulation varied across commodities and through time. For example, Wilson estimated the effects of deregulation as being positive for coal, but negative for farm products. A initial negative effect was estimated for 12 of 34 commodities, indicating that rate reductions were realized for shippers of these commodities. The remaining 24 commodities show a positive effect from deregulation, indicating these shippers might have face increased rates or that increased markups dominated cost savings during the initial

---

[33] Essentially, these conditions might include distance to barge transportation, industry concentration, or other conditions that vary across regions or over time. Variations by commodity will be captured in the intercept coefficient, while those conditions that vary time across commodities will be observable in the coefficient estimate for the variable year.

period of deregulation. However, an important finding from this study was that intertemporal effects of deregulation were negative for nearly all commodities.

The analysis conducted by Wilson also measures the direct and total effect of deregulation on rates, where the direct effect was measured from the regulation dummy variables and the total effects included the other explanatory variables, such as average length of haul, average load, and density. These measures suggested the largest effect of deregulation was captured in the direct effect, which would reflect price and technological changes.

A variety of different approaches for estimating rail rates have been described above. The methods used in this literature vary by the type of data used (aggregate versus disaggregate), the core objective of the study, and the complexity of the models developed for estimation. Early studies typically relied on the use of aggregate data and simple model specifications, while later studies embraced concepts and techniques embedded in NEIO, and sought to estimate more complex models using disaggregate data. In all cases, however, the models have been developed primarily for purposes other then the analysis of costs. En route to examining the specific issues, authors have used a wide range of specifications which we summarize in Table B.1 according to cost and markup variables.

A central objective of Section 4 of this report is to use this framework not to evaluate the effects of intra or intermodal competition or the effects of partial deregulation, but to estimate the parameters of a cost function, and then use that cost function to simulate costs and compare them to URCS generated cost estimates. The primary advantage of this approach is that it begins with disaggregated data i.e., the dependent variable is the rate for a specific movement between specific locations. We rest heavily on the previous research for specifying variables and in estimating the models.

TABLE B.1 A SUMMARY OF PREVIOUS SPECIFICATIONS

Author	Cost Variable Specifications	Mark-up Variable Specifications
Boyer (1987)	Average weight of freight trains (WEIGHT); Time/Year trend (TIME/YEAR)	Deregulation dummy (DEREG)
Barnekov and Kleit (1990)	Average weight of train (WEIGHT); Average length of haul (HAUL); Percent of bulk commodities (BULK); Time trend (YEAR) ; Fuel prices (FUEL)	Deregulation dummy (DEREG); Real truck rates (TRUCK)
McFarland (1989)	Traffic density (DENS); Average length of haul (ALH); Share of bulk loads (BK); Time trend (T);	Business activity (GNP); Deregulation dummy (DR); Interaction term, DR*T, (TR);
McDonald (1987)	Miles/distance of shipment (MILES); Tonnage of shipment (TONS); Annual tonnage shipped (VOLUME);	Miles to water (MIWATER &PORT); 1/Herfindahl index (RRCOMP); State regulation dummy (INTRA); Quarterly dummies
McDonald (1989)	Same as McDonald (1987), plus: Tons per car (TONS/CAR)	Same as McDonald (1987), plus: Year dummy variables for 1982-1985
Burton (1993)	Miles between shipment points (MMILES); Tons in shipment (MTONS); Number of line interchanges (MNINT); Overall volume of rail traffic (DENSITY); Changes in factor productivity & prices (TIME)	Index of distance to waterway (WATER); Number of carriers offering service (DIRSRV); Economic activity level (AVPROD); Interaction terms w/ dummy variable for deregulation (STAGG)*each RHS variable
Wilson (1994)	Average length of haul (ALH);Overall volume of rail traffic (DENSITY); Linear time trend (YR); Average load (AL)	Effects of demand over time (GDPG); Effects of deregulation overtime (STAG/STAGYR);
Wilson and Bitzan (current paper)	Miles/distance of shipment (MILES); Number of cars in shipment (NUMCAR); Tons per car (TONSCAR); Time trend (TREND);	Miles to water (MIWATER); 1/Herfindahl index (RRCOMP); State regulation dummy (INTRA); Quarterly dummies; Origin/terminating state dummies

Appendix C. Networks and Cost Models

As is noted regularly in the academic literature, railroads produce under a network technology. The network consists of a set of nodes which are or can be connected through a series of links. Outputs are flows of various commodities over the network. The standard approach in economics is to specify a technology, minimize costs and then estimate a cost function which is "dual" to the underlying technology. Such an approach takes the form theoretically as:

$$\min_{X_i} C = \sum_i w_i X_i \qquad s.t. \quad Q = f(X_i)$$

where w_i, X_i, Q, and $f(X_i)$ are factor prices, the level of inputs, the level of output, and the "production" function, respectively. Under appropriate regularity conditions, there exists a well defined cost function which yields the lowest cost of producing an output level (Q) given the technology (i.e., the parameters of the production function) and input prices (assuming no fixed factors). A commonly used result over the last 25 years or so is to estimate the cost function with a set of factor demand (or share) equations. That is, by Shephard's lemma, the derivatives of the cost function with respect to factor prices yields the conditional demands for the inputs (e.g., labor, capital, fuel) which share the parameters of the cost function. Their inclusion generally provides for very precise estimates of the shared parameters. Thus, in a standard "textbook" model, the system takes the form:

$$C = C(Q, w)$$

$$X_i^* = \frac{\partial C(Q, w)}{\partial w_i} = X_i^*(Q, w)$$

where X_i^* is the cost-minimizing demand for input i given output, factor prices and the technology.

The standard "textbook" case has been the basis for much of the econometric work conducted in the area since the early to mid-1970s, and our work below follows this same vein. In the development of this literature, there have been a few "modest" attempts to capture network effects, but to our knowledge, there have been no empirical studies that allow for explicit representation of multiple outputs defined as origin-destination-commodity (O-D-C) triples. Theoretically, the direct representation of network effects follows with some modifications to the "textbook" model. We provide a short illustration of such a model to reflect the ideal of a costing methodology. Specifically, a theoretical model of network costing is tractable, however, for most observed networks, the theoretical model in its most general form is not tractable. Econometric practice then is a tradeoff between theoretical considerations and economic reality with econometric tractability.

We begin with a network that consists of a set of nodes and links connecting the nodes. Following Spady (1985), transportation is produced by entry at a given node followed by a series of flows over the network to a terminal node. Outputs at a node include local cartage services, local gathering of shipments, switching, and distribution. Links allow the movement of goods from one node to another. It is generally well recognized that different firms have different networks both in terms of characteristics of the physical plant (rail lines, road bed, switching yards, etc.) and in network configuration (the level of connectivity, the length of the nodes etc.).

In illustrating a model of networks and costs, there are a number of network features to consider. For this illustration, we assume there is a single network with N nodes. The set of potential demands between N nodes is the "market" set, and a demand flow (q_{ij} is the movement of a commodity from node i to node j (where i and j are not necessarily adjacent nodes). Demand flows are directional, meaning that q_{ij} is a different demand flow from q_{ji}. In this structure, there are N^2 possible demands over a network of N nodes. The demand flows can be represented in a matrix, termed the demand matrix, given as:

$$Q = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1N} \\ q_{21} & & & \\ \cdots & & & \\ q_{N1} & \cdots & & q_{NN} \end{bmatrix}$$

From a firm's perspective, production occurs at the individual node and link components of the network subject to the constraint that a particular demand flow can be serviced. Define z_{ij} as a flow from node i to node j where i and j are "directly" connected i.e., requires no production activities at another link. For a fully connected network, the form of the activity matrix and the demand matrix are the same.

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1N} \\ z_{21} & & & \\ \cdots & & & \\ z_{N1} & \cdots & & z_{NN} \end{bmatrix}$$

The firm then finds the optimal routing of demand flows through the network to arrive at a "textbook" analog of the network costing approach which can be a fairly difficult problem depending on functional forms, subadditivity and scope.[34] However, often there is more structure that can be placed on the model. First, the Z matrix is for a fully connected network. Most networks are not fully connected. Not fully connected means that a node may not be "reachable" from another with the result that a demand flow cannot be serviced. Second, a node may be "reachable," but only through a series of connected activity flows. Now it is this structure that we consider. To do so, we describe two related graph theory concepts – the adjacency

---

[34] Subadditivity means that one firm can produce a given set of outputs more cheaply than two or more firms producing any combination of the given set of outputs. Economies of scope is a more refined concept in which one firm can produce a given set of outputs more cheaply than can two or more specialized firms, each producing a subset of products. For example, in the case of two outputs (A and B), a firm that produces a quantity of A and B can produce them more cheaply than can two firms wherein one firm produces only A and the other only B.

matrix (A) and the reachability matrix (R). The adjacency matrix is a square matrix of size (N) consisting of elements of zeros and ones. A particular element (a_{ij}) takes a value of one if there is a direct link between nodes i and j. The reachability matrix is of the same form, and in fact, is derivable from the adjacency matrix.[35] Elements of the reachability matrix also take values of zero and one. An element, r_{ij}, takes a value of one if the mode can be reached through a sequence of activity flows. That is, the element takes a value of one if through some routing it can reach the terminal node.

Given these two matrices, the constraints and choices of a firm are fairly complicated. First, the Schur or Hadamard product of the adjacency matrix (A) with the flow matrix (Z) reflects the link activities that are feasible over the N nodes – the flow feasibility constraint. For example, this product simply says that a direct activity flow (z_{ij}) cannot occur unless the firm has a direct link connecting nodes i and j. We write this link feasibility constraint as $Z_C = Z¶A$ where ¶ represents the Schur or Hadamard product operator. Second, the "service constraint" indicates whether a firm can even satisfy a particular demand flow with *any* sequence of flows. In this case, the set of serviceable demands is given by $Q_C = Q¶R$.

Now given these two sets of constraints, there is an ability to directly reflect the networks of firms in an economic optimizing framework. In the optimization, we first model firms as choosing input to minimize costs given flows over the network. This follows directly from the textbook model amended appropriately for multiproduct activities. Specifically, the model is:

$$\min_{X_i} C = \sum_i w_i X_i \qquad s.t. \quad T(Z, X) = 0$$

where $T(Z,X)$ is a transformation function representing technology (apart from the network constraints), Z is a vector of outputs where z_{ij} is a flow from node i to node j, and X is, as before, a vector of inputs. The result of this optimization yields a cost function not unlike that introduced by Spady (1985) i.e.,

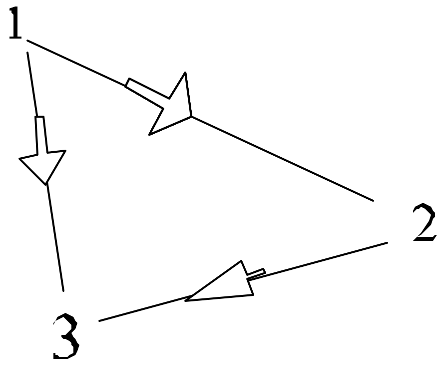
$$C = C(Z, w)$$

Given this cost function (the minimum costs of producing Z flows) over the network, the next step is to examine just how demand flows if it can. To do this, requires the link feasibility and the serviceability constraints be embedded into an optimization framework. These two constraints set what is feasible to the firm – what links can be used to service outputs and what demands can be serviced. A third type of constraint is implied by the flow and serviceability constraints is referred to here as the family of routing constraints. Associated with each serviceable demand flow is a non-empty set of routing alternatives. That is, a serviceable demand flow may be satisfied by one, two or more routing alternatives. In the event of two or more, embedded in firm's choices is the routing choice.

---

[35] The reachability matrix is technically defined as $R = A + A^2 + ... + A^N$ where the A^p is the adjacency matrix raised to the *pth* power. Further, the addition is defined in a Boullean algebra sense i.e., 1+1=1, 1+0=1, 0+0=0.

For example, suppose there is one serviceable demand that is non-zero (q_{13}) in a network (all other demands are zero) with three nodes graphically portrayed as:



In servicing this demand, the firm has two routing options. It can go directly from node 1 to 3 or indirectly from 1 to 3 via 2. These form choice variables of the firm. In this case, the set of activities that can service the demand can be written:

$$RoutingOption\,1: \qquad z_{11}=q_{13,}\, z_{13}=q_{13},\, z_{33}=q_{13}$$

$$RoutingOption\,2: \qquad z_{11}=q_{13,}\, z_{12}=q_{13},\, z_{23}=q_{13},\, z_{33}=q_{13}$$

The cost minimization problem becomes:

$$\min_{z_{ij}} C=C(z_{11},z_{12},z_{13},z_{21},z_{22},z_{23},z_{31},z_{32},z_{33}) \qquad s.t. \quad \begin{array}{l} z_{11}\le q_{13,}\, z_{13}\le q_{13},\, z_{33}\le q_{13} \\ z_{11}\le q_{13,}\, z_{12}\le q_{13},\, z_{23}\le q_{13},\, z_{33}\le q_{13} \\ z_{ij}\ge 0 \end{array}$$

There are many possibilities including: 1) Routing choice 1 is used for the entire quantity; 2) Routing choice 2 is used for the entire quantity; and 3) A linear combination of routing choice 1 and 2 are used. In each case, costs reduce to a comparison of routing choices wherein the third choice involves an optimal allocation between the two routing choices. In each case, costs are given by:

Route 1: $C^1=C^1(q_{13}, 0, q_{13,} 0, 0, 0, 0, 0, q_{13})$;

Route 2: $C^2=C^2(q_{13}, q_{13}, 0, 0, q_{13}, q_{13}, 0, 0, q_{13})$;

Route 3: $C^3 = C^3(q_{13}, (1-\lambda^*)q_{13}, \lambda^* q_{13}, 0, (1-\lambda^*)q_{13}, (1-\lambda^*)q_{13}, 0, 0, q_{13})$

where λ^* represents a choice of the firm on the optimal allocation of q_{13} between routes 1 and 2.[36]

Presentation of this model is intended to illustrate the complexity of network economics for application in rail costing. While this model can be extended for greater outputs and more complicated networks[37], it suffices to note that for railroad networks, theoretical and empirical estimation of this general model become quite complex. Specifically, with the addition of greater numbers of demand flows, commodities and more complicated networks, comes the need to examine the effects of not just scale but also scope and subadditivity issues which can obviously affect the routing choices made by the firm. In this simple illustration, there are nine potential flows. In this form, the estimation proceeds with nine outputs, factor prices and other network/operating characteristics. For most data sets, this structure does not lend itself to estimation of a cost function with any degree of flexibility; e.g., a translog, Diewert, miniflex, etc. are all likely not tractable with most data sets that are available.

While the intuitive appeal of such an approach is appealing from a theoretical perspective i.e., the marginal cost of a movement becomes a relatively simple matter that evolves directly from the model, the tradeoff between economic theory and econometric tractability becomes too large. The number of nodes in typical railroad networks is large and the number of commodities hauled by railroads also is large, with the result that the number of outputs (and potential outputs) becomes extremely large.[38] Thus, economists resort to aggregations of link/demand flows to measure output in econometric practice.

Spady (1985) introduces an "indexed" quadratic cost function which may be useful in econometric analyses of the cost model presented above, if sufficient data were available. He extends, the quadratic cost function introduced by Baumol, Panzer and Willig (1982) to allow aggregation of outputs. The quadratic cost function is given by:

$$C = a_0 h_0(p) + \sum_k a_k h_k(p) z_k + \sum_k \sum_m a_{km} h_{km}(p) z_k z_m$$

where the $h(p)$ functions are all homogeneous of degree one in the factor prices. In Spady's extension, he shows the cost function can be rewritten as:

---

[36] More formally, this is a constrained optimization problem wherein routes 1 and 2 are corner solutions and route choice 3 is an interior solution. In that light, λ^* takes a value between zero and one and represents the proportion of the output which is provided through route 1 and $(1-\lambda^*)$ represents the proportion of the demand sent through route 2.

[37] Indeed, Wilson (1985) provides such a generalization of this model using graph theory in conjunction with linear algebra in a cost minimization framework.

[38] A brief example is illustrative. Using the waybill data from 1983 through 2000, we calculated the number of unique origins (using the origin Standard Point Location Code (SPLC) of the originating station)) and unique destinations (terminal SPLC) and the unique combinations. There were 6250 unique origins, 3558 unique destinations, and 80,705 unique pairs in the data *for farm products alone* (Standard Transportation Commodity Code level 2 code equal to 1). These are calculated only for observed movements. Many more exist for potential movements.

$$C = n\ \left[C(\bar{z}, p) + 1/2\sum_k \sum_m a_{km} h_{km}(p) s_{km}\right]$$

where $\bar{z}$ is the average output across the multiproduct output vector, and s_{km} is the covariance of outputs *k* and *m*. Essentially, this result can be interpreted as the costs are n (the number of different outputs) operating under average conditions plus a differential reflecting departures of outputs from the average conditions. As he points out, there may be a number of circumstances in which the covariances are zero.

The dimensionality issue remains. In Spady's discussion, he divides production into on and off network activities, and for on network activities he makes a distinction between node (e.g., switching) and link(line haul). Under the assumption that the nodes and links have the same indexed quadratic cost functions, the first and second moments of the node and link activities are sufficient statistics for network activities. Under these assumptions, the multiproduct cost function is:

$$C = \sum_n C_N(y^n,\ t^n,\ p) + \sum_l C_l(y^l,\ t^l,\ p) + non - network \cos ts$$

where: C_N, and C_l are node and link cost functions common to all nodes and links, respectively; y^n is the total flow of node *n* and y^l is the total flow on link *l*; t^n and t^l are characteristics of the node n and link l, respectively. Such an approach has considerable promise in principle since it is tractable empirically using the earlier result, although it is arduous for large networks. Data requirements include a survey of a given networks links and node activities and characteristics. A difficulty of the approach is the additive separability of separate node and link activities e.g., node i costs do not depend on node j activities or the activities on link k.

There are many lessons that can be learned from this Section. First, the theoretical ideal for costing individual movements over a network emanates directly from theoretical principles. Explicit representation of network characteristics are easily represented in a general sense but may be difficult to implement. The routings, however, do give rise to network flows. These network flows, we assert, strongly may be affected by economies of scale/density and by cost complementarities over the network. Second, the sheer magnitudes of typical railroad networks and commodities makes econometric implementation of a such a general model not currently tractable, except under strong assumptions relating to economies of scale/density and separability of link cost functions. Such assumptions allow aggregations of network flows. Third, the approach suggested by Spady allows the estimation of a network cost function. In this regard, his model specifies costs as a function of aggregated link and node cost functions with common parameters (a special case of the more general model). While this reflects significant structure on the model, econometric implementation of this model may add dramatically to our knowledge of network technologies and, at the same time, provide a foundation under which movement costs are estimable. Unfortunately, to our knowledge, such an approach has not been implemented and represents an important area of future research.