ESSAYS IN TRANSPORT ECONOMICS

by

BRETT GABRIEL GARCIA

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Student: Brett Gabriel Garcia

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This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Economics by:

Wesley W. Wilson	Chairperson
Keaton Miller	Core Member
Jeremy Piger	Core Member
Anne Parmigiani	Institutional Representative

and

Andy Karduna	Interim Vice Provost of Graduate Studies

Original approval signatures are on file with the University of Oregon Division of Graduate Studies

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DISSERTATION ABSTRACT

Brett Gabriel Garcia

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Transportation plays an important role in economic growth and development, as it interacts with almost all other industries. Whether it be through barge, rail, road, or air, shippers are charged a price to have a commodity transported between an origin and destination, and transportation firms incur costs in facilitating the movement. However, there is a geographic nature inherent in transport networks that tends to result in varying degrees of market concentration, which impacts the prices and costs of the shipment. As a result, there exists a lengthy and ongoing debate regarding whether and how policymakers should intervene in these markets.

While transport is indeed essential to many sectors, the relative use of competing modes of transport has evolved over time due to changes in technology, public opinion, and public policy. As market participants adapt to these changes, they rely on accurate measures of market conditions to help guide their operational decisions. Accurate forecasts are needed to analyze past, current, and future operational needs. Reliable measures of shipment costs are needed by both regulators and market participants to help set shipment prices and evaluate the reasonability of these prices. Models that relate prices, costs, and markups to the presence of transport competition are needed to understand how market participants respond to changes in market conditions.

In this dissertation, I discuss my research investigating the industrial organization of transport markets in the United States. The dominant theme of my dissertation is transport economics. In chapter two, I predict waterborne commerce levels using a Bayesian model averaging (BMA) approach. In chapter three, I develop and estimate a multiproduct cost function for railroads. In chapter four, I operationalize the multiproduct cost function to estimate rail markups and quantify how these markups relate to the presence of transport competition.

CURRICULUM VITAE

NAME OF AUTHOR: Brett Gabriel Garcia

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene, OR
University of Utah, Salt Lake City, UT
California State University Chico, Chico, CA

DEGREES AWARDED:

Doctor of Philosophy, Economics, 2021, University of Oregon
Master of Science, Economics, 2018, University of Oregon
Master of Science, Economics, 2016, University of Utah
Bachelor of Arts, Economics, 2011, California State University Chico

AREAS OF SPECIAL INTEREST:

Industrial Organization
Applied Econometrics

GRANTS, AWARDS, AND HONORS:

Graduate Teaching Fellowship, University of Oregon, 2016-2021

Kleinsorge Summer Research Fellowship, University of Oregon, 2020

Summer Teaching Fellowship, University of Oregon, 2017-2018

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CHAPTER I

INTRODUCTION

Transportation plays an important role in economic growth and development, as it interacts with almost all other industries. Whether it be through barge, rail, road, or air, shippers are charged a price to have a commodity transported between an origin and destination, and transportation firms incur costs in facilitating the movement. However, there is a geographic nature inherent in transport networks that tends to result in varying degrees of market concentration, which impacts the prices and costs of the shipment. As a result, there exists a lengthy and ongoing debate regarding whether and how policy-makers should intervene in these markets.

While transport is indeed essential to many sectors, the relative use of competing modes of transport has evolved over time due to changes in technology, public opinion, and public policy. As market participants adapt to these changes, they rely on accurate measures of market conditions to help guide their operational decisions. Accurate forecasts are needed to analyze past, current, and future operational needs. Reliable measures of shipment costs are needed by both regulators and market participants to help set shipment prices and evaluate the reasonability of these prices. Models that relate prices, costs, and markups to the presence of transport competition are needed to understand how market participants respond to changes in market conditions.

In this dissertation, I discuss my research investigating the industrial organization of transport markets in the United States. The dominant theme of my dissertation is transport economics. In chapter two, I predict waterborne commerce levels using a Bayesian model averaging (BMA) approach. In chapter three, I develop and estimate a multiproduct cost function for railroads. In chapter four, I operationalize the multiproduct cost function to estimate rail markups and quantify how these markups relate to the presence of transport competition.

In the second chapter of my dissertation, I use Bayesian techniques to develop nowcasts for the quantity of waterborne traffic in the United States in total and for the four primary commodities. These waterborne traffic levels are released with a considerable time lag, but yet are of current interest. Nowcasts (i.e. predictions of the waterborne traffic levels to be released based on other variables that are available) have been constructed using an array of different variables and techniques. However, the large number of potential predictor variables and changes in the distribution of traffic levels leads to both model and estimation uncertainty, which has likely hampered the accuracy of these existing nowcasts. I use BMA to create nowcasts, which confronts model and estimation uncertainty directly via the averaging of models with different sets of predictors. I also use rolling window techniques to account for possible changes in the nowcasting relationship over time. Based on a variety of evaluation metrics, I find that BMA substantially improves nowcast accuracy.

In the third chapter of my dissertation, I adapt and apply techniques for estimating multiproduct cost functions in the railroad industry. Historically, regulators have relied on an accounting cost allocation procedure to determine whether shippers are exploiting their market power and charging excessive rates. However, the current accounting cost allocation procedure is heavily criticized. In this application, I estimate the cost function using first and second moments of shipment and railway characteristics. Quadratic cost functions provide a solution to handle the large number of product-origin-destination combinations. Implementing the model in this way allows shipment specific costs to be estimated while also incorporating the shared network technology inherent in railway networks. Regulators can use this approach to screen for excessively high rail rates. Shippers can check to see if they may be eligible for rate relief. Railroads can operationalize this method to set competitive rates and avoid the dispute resolution process.

In the fourth chapter of my dissertation, I operationalize the multiproduct cost function to analyze prices, costs, and markups for differentiated rail networks. Regulators of the railroad industry are tasked with protecting shippers from excessive rates for shipments in which the railroad is market dominant, defined as an absence of effective competition from intramodal and intermodal competition. This task requires shipment costs at an extremely disaggregate level. The current regulatory accounting approach of allocating costs is heavily criticized and cost functions in the academic literature are generally highly aggregated. In this paper, I develop a method to measure costs and markups that retains their disaggregate properties. I then use these results to explore market dominance, wherein the markup and the presence of competition determine whether shippers may be eligible to contest the reasonableness of the rate. I find that a movement from rail monopoly to duopoly is associated with an average 6.8% decline in rail markups. The results suggest nearby ports decrease the impact of rail competition on rail markups. This approach can be operationalized by regulators and market participants to assess the reasonableness of a rate and to streamline and expedite market dominance inquiry.

CHAPTER II

NOWCASTING WATERBORNE COMMERCE: A BAYESIAN MODEL AVERAGING APPROACH

II.1 Introduction

Forecasts are important for planning purposes (Armstrong, 1985; Thoma and Wilson, 2004). While forecasts of future periods are of obvious use, it is often the case that data for contemporaneous or past periods are released with a substantial lag, making timely predictions of these periods also of value. These predictions of current or past periods for which data has not yet been revealed are called nowcasts. Nowcasting models have been developed in a variety of contexts, primarily in the nowcasting of macroeconomic variables.[1]

In this paper, I am interested in nowcasting U.S. inland waterway traffic. The United States' 25,000 miles of inland waterway navigation provides a viable alternative to freight transport by road or rail. This intricate system supports more than a half million jobs and delivers more than 600 million tons of cargo each year (Board, 2015). Reliable nowcasts of waterway traffic provide market participants additional time to allocate resources. For example, nowcasts help planners at the U.S. Army Corps of Engineers to monitor waterway congestion and to evaluate whether investments are warranted. These nowcasts are also used by barge operators to monitor

[1]See for example Giannone et al. (2008), Camacho and Perez-Quiros (2010), and Giusto and Piger (2017).

congestion, allowing these firms to make employment decisions, gauge equipment needs, and adjust their rates to compete with alternative modes of transportation. Finally, government agencies can use nowcasts to validate trends and assess the quality of the data collection efforts.[2]

In the case of waterway traffic, the Waterborne Commerce (WBC) data is the official data to measure waterway flows; however, it is released with lag which can be long and uncertain.[3] A second data source provides more timely information on waterway flows, namely the Lock Performance Monitoring System (LPMS). The LPMS provides data on tonnages moving through each of the 164 locks in the inland waterway system, essentially providing 164 coincident variables that can be used to predict the eventual WBC release.[4]

While the LPMS data provides a rich dataset to nowcast the WBC data, the large number of variables provided in the LPMS presents a challenge for developing a nowcasting model that incorporates these variables. When faced with such a large set of potential predictor variables, there will exist substantial uncertainty over the correct set of variables to include in the model. Specifically, in my application, there exists over 4.7×10^{49} potential models to consider, where a model is defined as a particular set of predictor variables to include. One approach to proceed in the face of this model uncertainty is to select a particular subset of variables to include in the nowcasting model, perhaps through data-based methods. However, this ignores relevant information contained in omitted variables. An alternative approach, which would not omit information, is to simply include all potential predictor variables in the nowcasting

[2]The Army Corps reports nowcasts of inland waterway traffic using traditional methods on `https://www.iwr.usace.army.mil/Media/News-Stories/Article/494590/waterborne-commerce-monthly-indicators-available-to-public/`

[3]The source of WBC data are vessel company reports to the US Army Corps `https://www.iwr.usace.army.mil/about/technical-centers/wcsc-waterborne-commerce-statistics-center/`

[4]The LPMS data are recorded by the lockmaster for each of 164 locks and are readily available at `https://corpslocks.usace.army.mil/`
They differ in mode of collection and what they record `http://www.iwr.usace.army.mil/ndc/index.htm`.

model. However, with a large number of variables, this approach will typically lead to substantial estimation uncertainty, and thus inaccurate nowcasts. This is especially the case when samples sizes are limited and/or variables are highly correlated. Further complicating matters is that traffic shifts over the network through time may change the the set of predictor variables best explaining the waterborne traffic data.

Bayesian methods are attractive in settings that include significant model uncertainty, as they provide a straightforward, intuitive, and consistent approach to measure and incorporate model uncertainty when estimating parameters and constructing forecasts. BMA confronts these issues by averaging forecasts produced by each candidate model included in the model space. Averaging is accomplished using weights equal to the Bayesian posterior probability that a particular model is the correct forecasting model. Thus, models that are deemed by the data to be better forecasting models will receive higher weight in producing the BMA forecast. BMA also provides posterior inclusion probabilities for each explanatory variable, a useful measure of which predictors provide the most relevant information for constructing forecasts.

In this paper, I adapt and apply these techniques to nowcast WBC tonnages in total and for the four primary commodity groups in the United States. As potential predictor variables we use the LMPS data for each of the 164 locks, as well as lags of macroeconomic variables. I first provide in-sample estimation results constructed from data covering January 2000 to December 2013. These results demonstrate that there is substantial uncertainty regarding which predictor variables belong in the true nowcasting model, as the model probabilities are spread over a very large number of possible models. This provides empirical justification of the use of BMA techniques in our setting. I then conduct an out-of-sample nowcasting experiment extending from January 2011 to December 2013. To account for possible changes in the composition of movements over the inland waterway network throughout time, I re-estimate the models on a rolling window prior to forming each out-of-sample nowcast. The results suggest that the BMA procedure combined with the rolling-window estimation provides very accurate nowcasts, improving substantially on the accuracy of existing studies that produced nowcasts of waterborne commerce data.

This paper fits into a larger literature that explores forecasting and nowcasting transportation data. Babcok and Lu (2002) construct an ARIMAX model to explore the short-term forecasting of inland waterway traffic using data for grain tonnage on the Mississippi River and find their model provides accurate forecasts. Tang (2001) develops an ARMA model to forecast quarterly variation for soybean and wheat tonnage on the McClellan-Kerr Arkansas River. She finds that incorporating structural breaks into the model allows it to provide more accurate forecasts. Thoma and Wilson (004a) analyze shocks to barge quantities and rates from changes in ocean freight rates, and rail rates and deliveries. The authors use vector autoregressions and variance decompositions with an application to weekly transportation data. Thoma and Wilson (2004) estimate the co-integrating relationships between river traffic, lock capacities, and a demand measure from 1953 through 2001. Forecasts of river traffic are developed based on the co-integrating relationship over an extended period of time. Thoma and Wilson (2005) explore the value of information contained in the LPMS data for nowcasting WBC values. They use annual data to identify key locks with pair-wise correlations and step-wise regressions, including these as predictors for annual WBC tonnages. My paper contributes to this literature by introducing BMA to forecasting transportation networks.

The remainder of the paper proceeds as follows. Section 2 describes the data and provides an example of waterborne commerce movements. Section 3 outlines the general nowcasting model and describes the Bayesian Model Averaging approach to construct nowcasts. In Section 4 I present results regarding which predictor variables are most relevant for constructing nowcasts, as well as results from the out-of-sample nowcasting exercise. Finally, Section 5 provides some discussion and concluding remarks.

II.2 Background

In this section, I first describe the waterway system and the location of the lock system. The U.S. inland and intracoastal waterways system's 25,000 miles of navigable water directly serve 38 states and carries nearly one sixth of all cargo moved between cities in the United States. The Gulf Coast ports of Mobile, New Orleans, Baton Rouge, Houston, and Corpus Christi are connected to the major inland ports of Memphis, St. Louis, Chicago, Minneapolis, Cincinnati, and Pittsburgh via the Gulf Intracoastal Waterway and the Mississippi River. The Mississippi River is essential to both domestic and foreign U.S, trade, allowing shipping to connect with barge traffic from Baton Rouge to the Gulf of Mexico. The Columbia-Snake River System provides access from the Pacific Northwest 465 miles inland to Lewiston, Idaho (ASCE, 2009).

In Figure II.1, I map the lock locations by river. As is evident in this figure, the locks that comprise the LPMS are concentrated in the Midwest and Southeast regions of the country. The majority of inland waterway commerce is concentrated along the Ohio River and the Mississippi River. The various geographic origins of each commodity and changes in demand for these commodities likely influence traffic patterns over time. Coal is the largest commodity by volume transported along the inland waterway system but its role has been declining as natural gas has become more attractive. The decline in demand for coal is likely to influence traffic patterns, which could potentially impact which locks provide the most valuable information in predicting WBC flows.

Figure II.1
Lock Location by River

II.2.1 Data

I next describe the sources and characteristics of the Waterborne Commerce (WBC) data and the Lock Performance Monitoring System (LPMS) data. The WBC data are developed from monthly reports of waterway transportation suppliers, and measure the tonnage by commodity group moved along the inland waterway system. Specifically, the WBC data measures tons traveling on all US rivers measured in total (all commodities), as well as for four commodity groups: food and farm product tons, coal tons, chemical tons, and petroleum tons. There is substantial processing associated with the WBC data, and its release time lags the data by a year or more. WBC data is highly accurate and is considered the industry standard. In contrast, the LPMS data records tonnages of commodities passing through specific inland locks, as recorded by the lock operator. It is available relatively quickly, typically within a month (Navigation Data Center, 2013.)[5] While the LPMS data and the WBC data

[5]The LPMS annual report in typically released in March, initial figures are made available on the US Army Corps website and can be accessed in real-time `https://corpslocks.usace.army.mil/`

measure different quantities, they are very much connected as shown below.

The dependent variable in my analysis is defined as WBC tonnage (overall or by specific commodity group) and is measured monthly for the years 2000-2013 as reported by the Waterborne Commerce Statistics Center. The predictor variables include the LPMS lock variables, provided by the Summary of Locks and Statistics, courtesy of the US Army Corps of Engineers Navigation Data Center's *Key Lock Report*. The report contains monthly total tonnage values measured for 2000-2013 for each of 164 specific locks in the system. These data were supplemented by employment statistics obtained from the US Bureau of Labor Statistics which provides data at the national level for years 2000-2013. Specifically, I include the two-month lag of the unemployment rate as an additional potential predictor.[6]

In Figure II.2, I present total commodity tonnage of the inland waterway network throughout time. Specifically, this figure details annual LPMS tonnage for total commodities moving along the two major rivers, the Mississippi and Ohio, as well as an Other category that accounts for tonnage along the remaining 26 rivers. That is, the value for each river represents the sum of all tonnages passing through all locks for a specific river. The fluctuations in LPMS tonnage along the Mississippi River can be attributed to seasonal fluctuations in river accessibility. Notice that the tonnages appear relatively stable.

In Figure II.3, I present commodity specific tonnage moving along the inland waterway network. The Ohio River facilitates the majority of coal movement along the network, accounting for 68% of all coal LPMS tonnage. The Mississippi River helps to distribute food and farm products throughout the country, accounting for 57% of all food and farm LPMS tonnage. Petroleum products tend to travel along the Gulf Intracoastal Waterway, with 43% of all petroleum products being transported

[6] I follow the literature and include the second lag of the unemployment rate rather only. The LPMS data is available for a given month more quickly than the unemployment rate. Using the second lag ensures that use of the LPMS data to nowcast the WBC data is not held up by unemployment data.

Figure II.2
LPMS Tonnage by River: Total Commodities

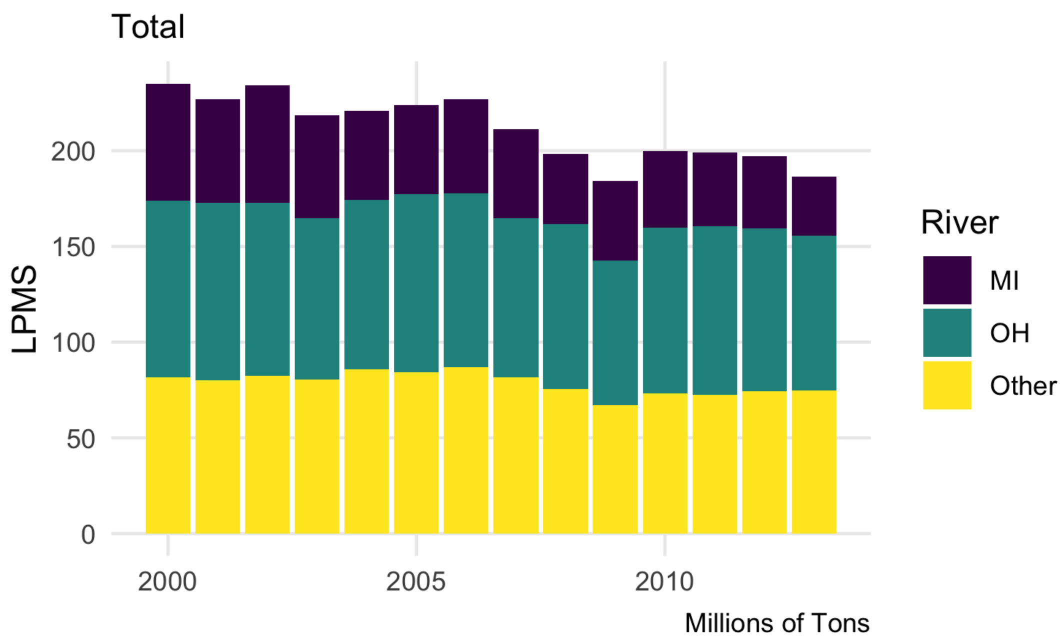
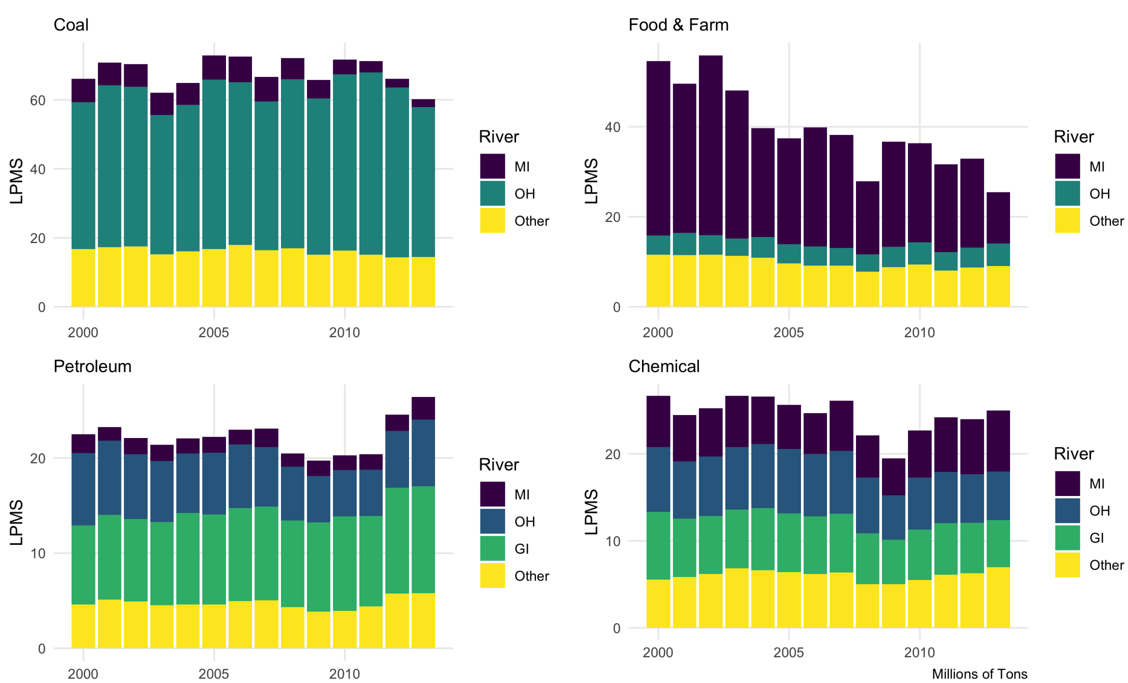


Figure II.3
LPMS Tonnage by River: Primary Commodities



through this system. Chemical tonnages appear to be evenly distributed amongst the Mississippi River, the Ohio River, and the Gulf Intracoastal Waterway, with 74% of all chemical LPMS tonnage traveling along these three rivers.

II.2.2 WBC via the LPMS

This paper uses LPMS data as a coincident indicator for WBC data. The WBC data are the result of firms filling out a monthly form, while the LPMS data are the result of lockmasters recording the tonnages and commodities at each lock. To illustrate the two types of data and how they are related, I follow Thoma and Wilson (2005) and present a stylized example that relates the LPMS data to the WBC data. The example demonstrates that changes in tonnages through key locks are useful for capturing changes in overall tonnages moving on the river. To clarify the differences and connections of the LPMS and WBC data, consider a river that has three locks labeled $L1$, $L2$, and $L3$. Suppose that during the time period that tonnages are measured, there are four barge loads that move on the river. The tonnages and movements between locks are:

Load 1	10 tons through lock $L1$
Load 2	30 tons through locks $L1$ and $L2$
Load 3	40 tons through locks $L1$, $L2$, and $L3$
Load 4	20 tons through locks $L2$ and $L3$

The WBC data measure the sum of all loads (in tons) moved on the river. Hence, the WBC measurement is $10+30+40+20 = 100$. The LPMS measurements reflect totals for each individual lock. For example, Load 3 has a total of 40 tons that travel through $L1$, $L2$, and $L3$. The LPMS data then records 40 tons for $L1$, 40 tons for $L2$, and 40 tons for $L3$. In contrast, the WBC data records 40 tons. The final LPMS data for the four loads described above is reported in Table II.1. The idea is to use the LPMS variables to capture changes in overall tonnage moving on the river by estimating a statistical model relating WBC to LPMS variables. Simply including all

Table II.1
LPMS Data Example (Tons)

Lock	L1	L2	L3
Load 1	10		
Load 2	30	30	
Load 3	40	40	40
Load 4		20	20
Totals	**80**	**90**	**60**

LPMS variables when the number of such variables is large is likely to be ineffective, as there will be substantial estimation uncertainty associated with the weights that should be given to the individual locks. Also, some locks are likely uninformative (or redundant) for total tonnage, suggesting that a nowcasting model should focus on a select group of key locks. Section 3 provides a more formal and consistent treatment using Bayesian techniques to identify key locks.

II.3 Empirical Model and Bayesian Model Averaging

II.3.1 The Nowcasting Model

In this section, I present the nowcasting models used to predict WBC values given LPMS data. I focus on linear candidate models that relate the WBC river tonnage in month t to the second lag of the unemployment rate, and some subset of the 164 lock tonnage variables provided by LPMS. Equation II.1 below is an example of one of approximately 4.7×10^{49} such candidate models that we could consider:

$$WBC_t = \beta_0 + \beta_1 UR_{t-2} + \beta_2 MI15_t + \beta_3 OH52_t + \varepsilon_t \tag{II.1}$$
$$\varepsilon_t \sim i.i.d.\ N(0, \sigma^2).$$

In Equation II.1, WBC_t is the relevant WBC variable (total tonnage or commodity specific tonnage) measured in month t, UR_{t-2} is the second monthly lag of the U.S. unemployment rate, $MI15$ is the total tons passing through lock 15 on the Mississippi River in month t, and $OH52$ is the total tons passing through lock 52 on the Ohio River in month t. In this example, there are thus two LPMS lock variables included in the model.

Estimating this model provides a way to quantify the relationship between specific locks and WBC flows. Note that although the left-hand side WBC variable and the right-hand side LPMS lock variables are measured for the same period, the LPMS variables are available far earlier than the WBC variable.[7] With the LPMS data released prior to the corresponding WBC data, the LPMS data serves as a coincident indicator to nowcast the WBC variables.

Equation II.1 includes a specific subset of LPMS lock variables as predictors, and thus represents one possible model that might be used to nowcast the WBC data using the LPMS variables. One could simply include all possible lock variables in the model, but this would lead to substantial estimation uncertainty and likely low quality forecasts. Indeed, for our dataset, if all potential predictor variables were included in the nowcasting model there would exist only three degrees of freedom, as we have 168 observations and 165 potential variables. Estimation uncertainty is further exacerbated by the fact that many of the LPMS lock variables are highly collinear. With only 168 observations, a parsimonious representation of the data is of vital importance in order to preserve the statistical power of the nowcast. However, exactly which representation should be used is unclear, meaning there is substantial model uncertainty.

[7]The timing difference between the releases is variable and uncertain, but can be as long as 1.5 years.

II.3.2 Bayesian Model Averaging

I consider linear regression models as in Equation II.1, where the models differ by the specific set of predictor variables included in the model. Again, these possible predictor variables include the 164 LPMS lock variables and the unemployment rate. Label a particular model as M_j, where a "model" consists of a choice of which variables to include in the linear regression typified by Equation II.1. Here, $j = 1, 2, \ldots, J$ and J is the number of possible models. Again, as discussed above, J is approximately 4.7×10^{49} in my setting.

With such a large number of possible models, as well as the relatively small sample size, there is significant uncertainty regarding the true model that should be used to form nowcasts. Here we take a Bayesian approach to compare and utilize alternative models. Specifically, the Bayesian approach to compare alternative models is based on the posterior probability that M_j is the true model:

$$Pr(M_j|Y) = \frac{f(Y|M_j)\ Pr(M_j)}{\sum_{i=1}^{J} f(Y|M_i)\ Pr(M_i)}\ ,\ \ j = 1, ..., J \tag{II.2}$$

where Y indicates the observed data, $Pr(M_j)$ is the researcher's prior probability that M_j is the true model and $f(Y|M_j)$ is the *marginal likelihood* for model M_j:

$$f(Y|M_j) = \int f(Y|\theta_j, M_j)\ p(\theta_j|M_j) d\theta_j$$

where θ_j holds the parameters of the j^{th} model, $f(Y|\theta_j, M_j)$ is the likelihood function for model M_j and $p(\theta_j|M_j)$ is the prior density function for the parameters of M_j. In words, the marginal likelihood function has the interpretation of the average value of the likelihood function, and therefore the average fit of the model, over different parameter values. The marginal likelihood plays an important role in Bayesian model comparison, as this term is increasing in sample fit, but decreasing in the number of parameters estimated. This penalty for more complex models naturally prevents overparameterization, an attractive feature for developing a nowcasting model.

The posterior model probability $Pr(M_j|Y)$ can be used to confront model uncertainty. For example, one could select the model with highest posterior probability and then construct nowcasts based on this best model alone. However, this focus on one chosen model ignores potentially relevant information in models other than the chosen model. This is especially important when the posterior model probability is dispersed widely across a large number of models. Instead of basing inference on the single highest probability model, BMA proceeds by averaging posterior inference regarding objects of interest across alternative models, where averaging is with respect to posterior model probabilities. For example, suppose I have constructed a nowcast for WBC_t from each model M_j, and I label these nowcasts $\widehat{WBC}_t^j$. I can then construct a BMA nowcast as follows:

$$\widehat{WBC}_t = \sum_{j=1}^{J} \widehat{WBC}_t^j \, \mathrm{Pr}(M_j|Y) \tag{II.3}$$

Another object of interest in this setting is the posterior inclusion probability, or PIP, for a particular predictor variable. Specifically, suppose I am interested in whether a particular predictor variable, labeled X_n, belongs in the true model. The PIP is constructed as:

$$PIP_n = \sum_{j=1}^{J} \mathrm{Pr}(M_j|Y) I_j(X_n) \tag{II.4}$$

where $I_j(X_n)$ is an indicator function that is one if X_n is included in model M_j and zero otherwise. In other words, the PIP for X_n is simply the sum of all the posterior model probabilities for all models that include X_n. This PIP provides a useful summary measure of which variables appear to be particularly important for nowcasting the WBC variable.

To implement the BMA procedure, I require two sets of prior distributions. The first is the prior distribution for the parameters of each regression model. When the space of potential models is very large, as is the case here, it is useful to use prior parameter densities that are fully automatic, in that they are set in a formulaic way across alternative models. To this end, I follow the strategy of Fernández et al. (2001) for setting priors for the parameters of linear regression models in BMA applications. These priors are designed for the case where the researcher wishes to use as little subjective information in setting prior densities as possible, and was shown by FLS to both have good theoretical properties and perform well in simulations for the calculation of posterior model probabilities. Additional details can be found in Fernández et al. (2001).

The second prior distribution I require is the prior distribution across models, $\Pr(M_j)$. Here, I use a prior suggested in Ley and Steel (2009), which is uniform with respect to model size. In other words, models that include the same number of predictor variables receive the same prior weight. Also, the group of all models that include a particular number of predictor variables receives the same weight as the group of all models that contain a different number of predictor variables. Further details can be found in Ley and Steel (2009).

While conceptually straightforward, implementing BMA in this setting is complicated by the enormous number of models under consideration. Specifically, the summation in the denominator of Equation II.2 includes so many elements as to be computationally infeasible. To sidestep this difficulty I use the Markov-chain Monte Carlo Model Composition (MC^3) approach of Madigan and York (1993). MC^3 proceeds by constructing a Markov-chain Monte Carlo sampler that produces draws of models from the multinomial probability distribution defined by the posterior model probabilities. It is then possible to construct a simulation-consistent estimate of $Pr(M_j|Y)$ as the proportion of the random draws for which model M_j was drawn. For this implementation of MC^3 I use one million draws from the model space, following 100,000 draws to ensure convergence of the Markov-chain based sampler. I implement a variety of standard checks to ensure the adequacy of the number of pre-convergence draws.[8]

II.4 Results

II.4.1 In-Sample Variable Inclusion Results

BMA constructs nowcasts as an average across models with different sets of predictors. To better understand the set of predictors and which are most useful in nowcasting WBC values, I apply BMA to the full sample of data extending from January 2000 to December 2013. In Table II.2, I report the top 10 models ranked by posterior model probability, both for the case where the dependent variable is total WBC tonnage and for the cases where the dependent variable is a specific commodity type. As Table II.2 makes clear, these top 10 models account for less than 2% of the total posterior model probability for all possible models. This suggests that the posterior model probability is spread across a very large number of models, highlighting the significant model uncertainty associated with our dataset. This also highlights the importance of the BMA approach, in that it incorporates the information contained in all models, rather than focusing on any single model that receives low posterior model probability.

Given the empirical relevance of BMA, I next present the PIPs in order to evaluate which locks appear most important for nowcasting WBC. The PIPs are calculated as in Equation II.4. Figures II.4 and II.5 displays the PIPs for total WBC tonnage in two different ways. In Figure II.4 the PIPs are presented via a map, where I focus on the main inland waterway network.[9] In Figure II.5, I present the posterior

[8]A textbook treatment of the MC^3 algorithm can be found in Koop (2003).

[9]The full map is presented in the Appendix Figure A.II.1.

Table II.2
Posterior Model Probabilities for Top 10 Models
$\Pr(M_j|Y)$

	Total	Coal	Farm	Petro	Chem
1	1.47	1.72	1.31	1.61	1.57
2	1.42	1.28	1.20	1.49	1.28
3	1.12	1.17	1.17	1.23	1.17
4	1.11	0.96	1.15	1.09	1.01
5	0.95	0.95	0.99	1.05	0.98
6	0.82	0.82	0.93	0.96	0.94
7	0.81	0.83	0.92	0.73	0.86
8	0.80	0.80	0.86	0.65	0.82
9	0.77	0.70	0.75	0.63	0.69
10	0.75	0.67	0.72	0.58	0.68

Note: Posterior model probabilities for top 10 highest probability models. All table entries should be multiplied by 10^{-7}

inclusion probability for all predictors via a bar chart. The horizontal axis displays each explanatory variable while the vertical axis measures the posterior inclusion probability. The explanatory variables are too voluminous to represent in the figure; however, the ordering follows the river names (Allegheny, Atlantic Intercoastal Waterway, Atchafalaya, Blackwarrior Tombigbee, Calcasieu, Chicago, Canaveral Harbor, Columbia, Cumberland, Freshwater Bayou, Green and Barren, Gulf Intracoastal Waterway, Illinois Waterway, Kanawha, Kaskaskia, Mississippi, Mc-Kerr Arkansas River Navigation System, Monongahela, Ouachita and Black, Old, Ohio, Okeechobee Waterway, Red, St. Marys, Snake, Tennessee, Tennessee Tombigbee Waterway) and lock number, with the final predictor representing the two-month lag unemployment rate. As two examples, the predictor with the largest posterior inclusion probability in Figure II.5 corresponds to the Kaskaskia River Navigation Lock (PIP = 0.9995), while the predictor with the second largest posterior inclusion probability corresponds to the Barkley Lock (PIP = 0.8099). This means that out of the models sampled by MC^3, the Kaskaskia Lock appeared as a predictor in over 99% of these models.

The results reveal that there exist several explanatory variables that have a high probability of being included in the true nowcasting model; however, the majority of locks have less than a 5% probability of being included in the model. This figure again highlights the advantage of the BMA approach relative to methods that select a particular model. All potential explanatory variables have a non-zero posterior inclusion probability, indicating that all explanatory variables appear in the nowcast. Out of the 1,000,000 draws taken as part of the MC^3 algorithm, the average model contains 14 explanatory variables. Hence, BMA is able to directly incorporate all explanatory variables into the nowcast, while also preserving statistical power. In Table II.3, I list the explanatory variables with the largest posterior inclusion probabilities. This table highlights the locks that help to predict WBC flows in total commodities. Of the 165 predictors considered, the BMA approach picks up eight locks that appear in at least half of the models sampled by MC^3. Note that the Kaskaskia River Navigation Lock has a posterior inclusion probability of 0.9995, which means that this lock appeared in over 99% of the models sampled by MC^3. This result is not surprising, as this lock is located in the free-flowing area of the Middle Mississippi River. That is, unlike the Upper Mississippi, which contains a series of locks and dams, the Middle Mississippi only contains this single lock. Additionally, the Middle Mississippi connects waterborne commerce between the Upper Mississippi and the Ohio River, the two largest river systems by volume. Hence, any waterborne commerce traveling between the Mississippi River and the Ohio River must travel through and be recorded in the LPMS tonnage of the Kaskaskia River Navigation Lock.

In Figure II.6, I display the commodity specific posterior inclusion probabilities for locks in the inland waterway network.[10] In Figure II.7, I present the commodity specific posterior inclusion probabilities for all predictors. The predictive ability of each lock varies by commodity, as expected due to the geographic variation in waterway routes. Similar to the results for total commodities, commodity specific

[10]The full map is presented in Appendix Figure A.II.2.

Figure II.4
Posterior Inclusion Probability Map: Total Commodities

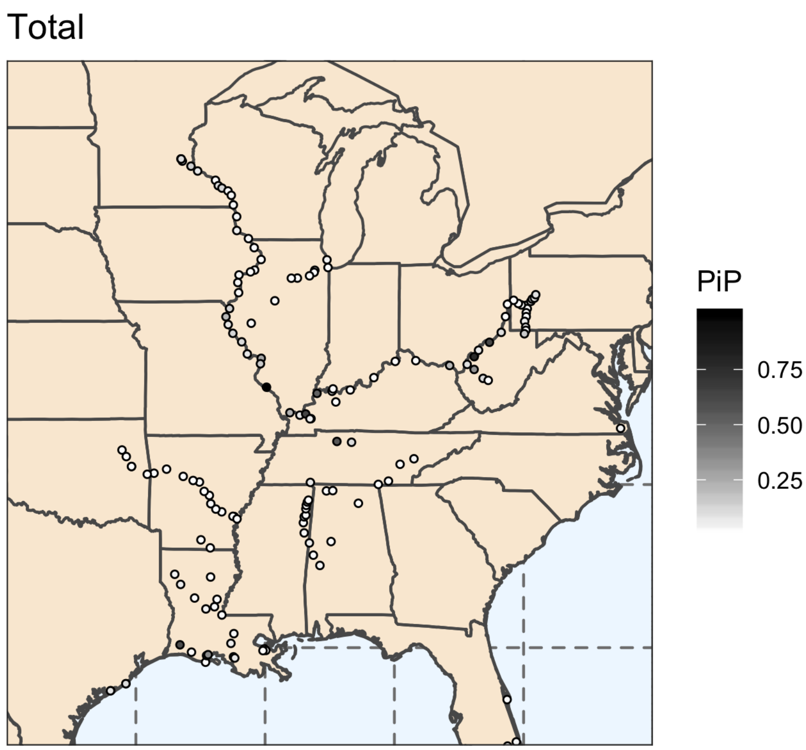


Figure II.5
Posterior Inclusion Probability Histogram: Total Commodities

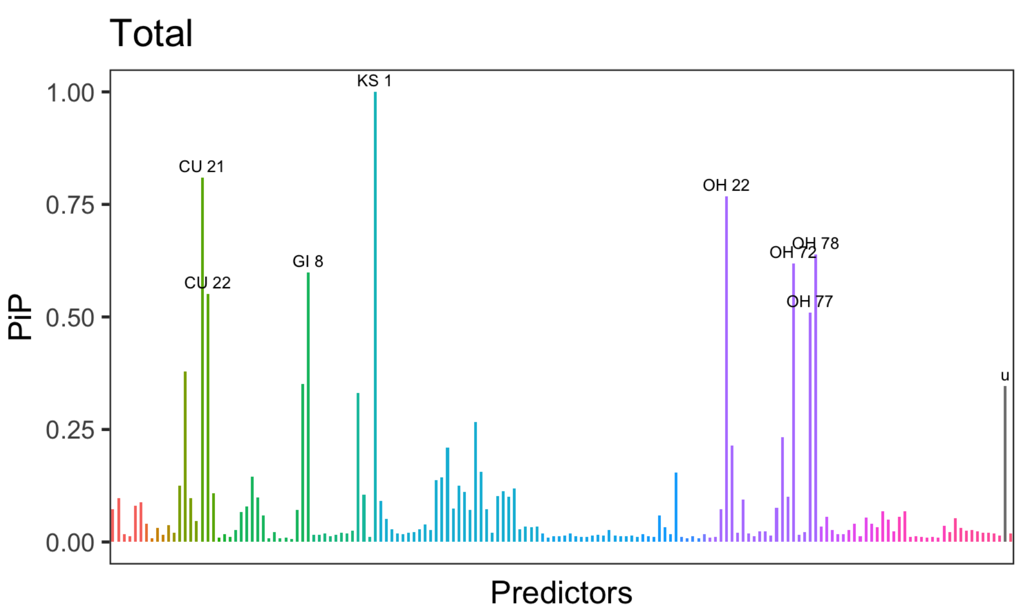


Table II.3
BMA Results - Total Commodities

Explanatory Variable	PIP	River
Kaskaskia River Navigation Lock	0.9995	Kaskaskia
Barkley Lock	0.8099	Cumberland
Racine Locks and Dam	0.7675	Ohio
Smithland Lock and Dam	0.6383	Ohio
Willow Island Locks and Dam	0.6187	Ohio
Calcasieu Lock	0.5982	Gulf
Cheatham Lock	0.5510	Cumberland
John T. Meyers Lock and Dam	0.5098	Ohio

Note: Results for the explanatory variables with PIP > 0.5.

posterior inclusion probabilities reveal substantial model uncertainty. For each commodity, there exist several locks that have a high probability of being included in the model; however, the majority of locks have less than a 5% probability of being included in the commodity specific model. Similar to the results for total commodities, commodity specific posterior inclusion probabilities for all explanatory variables are non-zero, revealing that all explanatory variables appear in the nowcast for each commodity.

In Table II.4, I present the commodity specific BMA results for the explanatory variables with posterior inclusion probabilities greater than 0.5. For each commodity, there exist different sets of locks that provide superior predictive ability. Note that the chemical results reveal a posterior inclusion probability of 0.9885 for the two-month lag unemployment rate, which means this variable appeared in over 98% of the models sampled by MC^3, providing evidence that the unemployment rate contains valuable information in predicting contemporaneous and future chemical WBC flows.

Figure II.6
Posterior Inclusion Probability Map: Primary Commodities

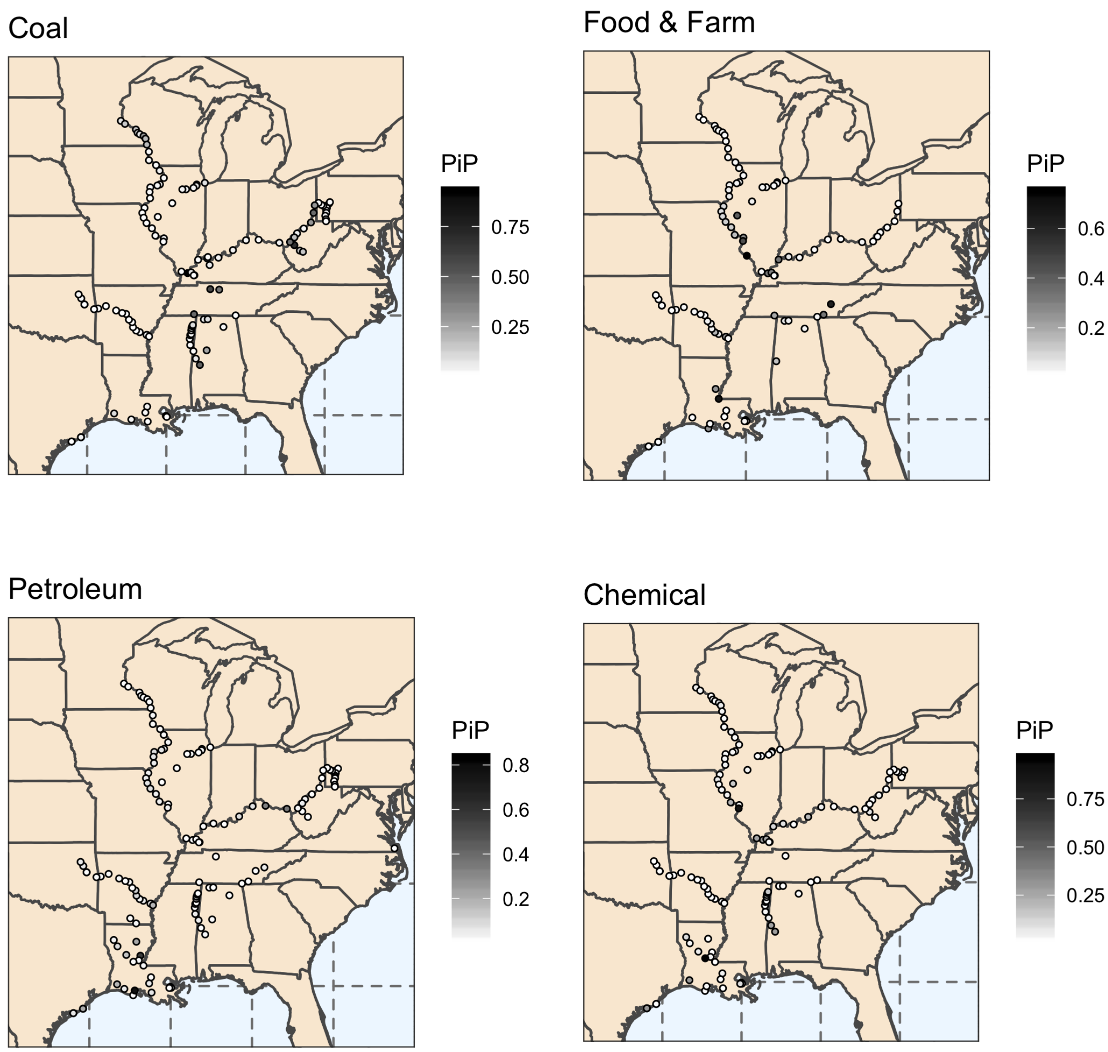


Figure II.7
Posterior Inclusion Probability Histogram: Primary Commodities

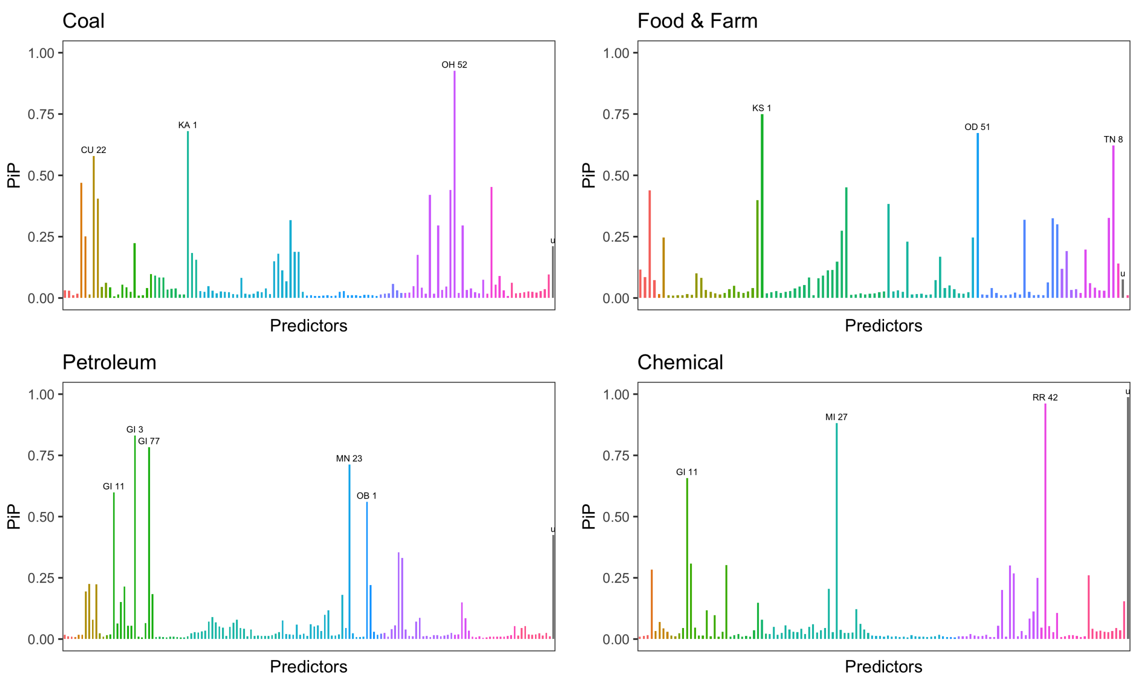


Table II.4
BMA Results - Primary Commodities

Commodity	Explanatory Variable	PIP	River
Coal	Lock and Dam 52	0.9261	Ohio
Coal	Winfield Locks and Dam Main 1	0.6804	Kanawha
Coal	Cheatham Lock	0.5787	Cumberland
Food & Farm	Kaskaskia River Navigation Lock	0.7489	Kaskaskia
Food & Farm	Old River Lock	0.6725	Old
Food & Farm	Watts Bar Lock	0.6221	Tennessee
Petroleum	Inner Harbor Navigation Canal Lock	0.8312	Gulf
Petroleum	Leland Bowman Lock	0.7830	Gulf
Petroleum	Lock and Dam 3	0.7126	Monongahela
Petroleum	Colorado River East Lock	0.5985	Gulf
Petroleum	Jonesville Lock and Dam	0.5605	Ouachita
Chemical	Unemployment Rate (two-month lag)	0.9885	
Chemical	John H. Overton	0.9619	Red
Chemical	Chain of Rocks Lock and Dam 27	0.8814	Mississippi
Chemical	Colorado River East Lock	0.6580	Gulf

Note: Results for the explanatory variables with PIP > 0.5.

II.4.2 Out-of-Sample Nowcast Results

This section provides results of an out-of-sample nowcast experiment using our BMA approach. To account for possible changes in the composition of movements over the inland waterway network throughout time, I re-estimate the models on a rolling window prior to forming each out-of-sample nowcast. That is, the model is estimated using data from January 2000 to January 2010 and then a BMA nowcast for January 2000 is constructed. Next, the model is re-estimated using data from February 2000 to February 2010 and then a nowcast for February 2000 is constructed. This process is repeated until we have nowcasts through December 2013.

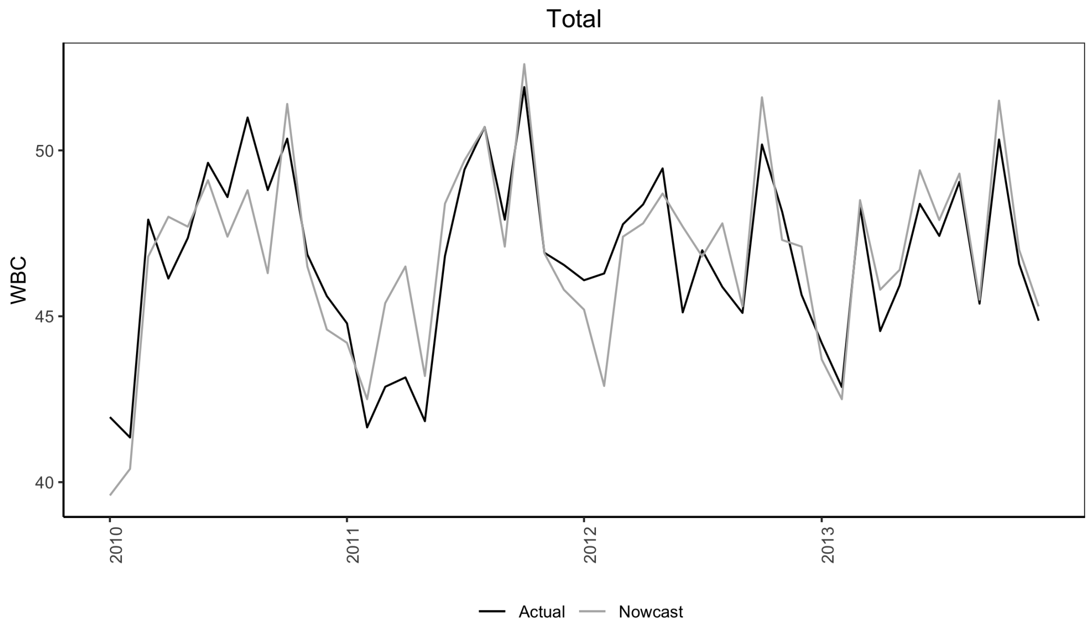
Figure II.8 visualizes the out-of-sample nowcast accuracy of the BMA approach for total WBC tonnage. This plot shows the WBC data relative to the WBC nowcast values for total commodities. Figure II.9 visualizes the out-of-sample nowcast accuracy of the BMA approach for specific commodities. These plots show the WBC data relative to the WBC nowcast values for each commodity. The BMA approach is able to predict close to the actual tonnage for total and for all primary commodities. The MC^3 algorithm is capable of providing accurate nowcasts while avoiding the problems associated with an overparameterized model.

Here, I present a summary measure of how well the BMA procedure performed at estimating the true WBC values at each point in time. Specifically, Table II.5 provides the mean squared error (MSE) for each commodity and Table II.6 provides the average percentage forecast error for each commodity. The MSE for the nowcast is calculated by:

$$MSE = \sum_{t=1}^{T} \frac{1}{T} (\widehat{WBC}_t - WBC_t)^2 \tag{II.5}$$

where $\widehat{WBC}_t$ is the BMA nowcast of WBC_t defined in Equation (3). The results indicate that the WBC values were estimated accurately by the BMA approach,

Figure II.8
Comparison of Actual WBC Tons to Nowcast WBC Tons: Total



with the largest MSE being 356.27, and all commodity specific MSE below 56.97.[11] Based on these nowcast evaluation metrics, I conclude that the LPMS data provides the most value for predicting contemporaneous values of chemical tonnage, where all MSE are below 8.66. These translate into average percentage forecast errors of less than 2.4% for total, 1.3% for coal, 5.7% for food and farm, 2.2% for petroleum, and 4.8% for chemical tonnages.

Table II.5
Nowcast Evaluation Metrics - MSE

Year	Total	Coal	Farm	Petroleum	Chemical
2010	257.76	19.67	46.87	56.94	8.66
2011	356.27	55.73	33.59	43.21	8.45
2012	228.02	32.08	35.79	37.00	5.60
2013	166.20	7.54	28.74	20.00	2.50

Note: Hundreds of thousands of tons.

[11]For MSE, I scale the units to hundreds of thousands of tons.

Figure II.9
Comparison of Actual WBC Tons to Nowcast WBC Tons: Primary

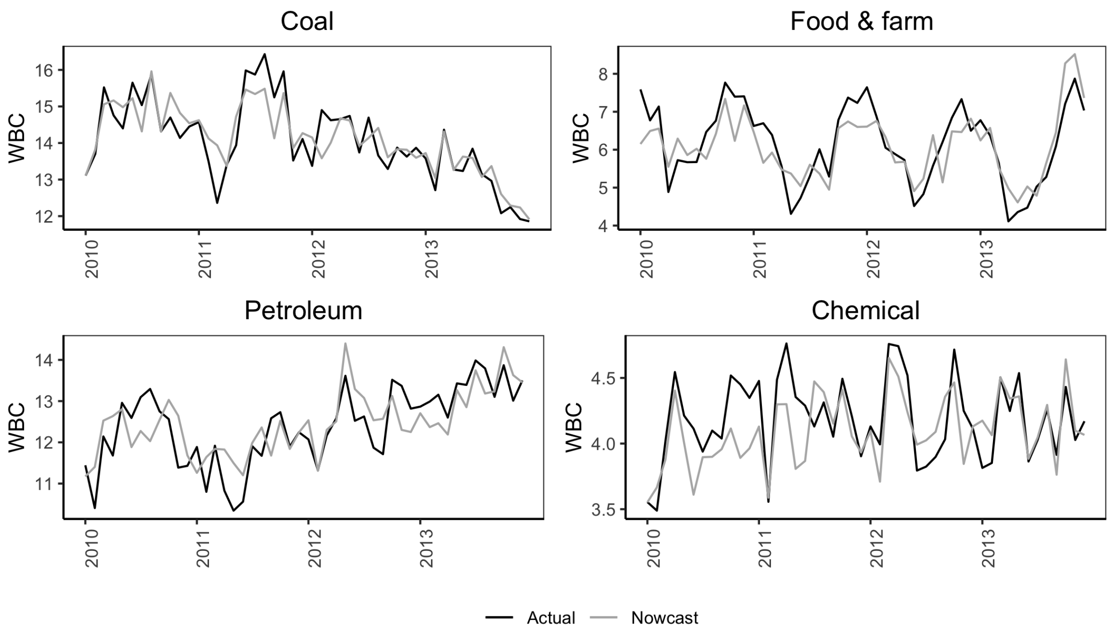


Table II.6
Average Percentage Forecast Error

Year	Total	Coal	Farm	Petroleum	Chemical
2010	1.98	-0.65	3.23	-0.94	4.75
2011	-2.31	-0.27	2.29	-2.13	2.95
2012	-0.34	0.28	1.08	-1.44	1.02
2013	-0.96	-1.23	-5.69	1.45	-1.27

II.5 Concluding Remarks

This paper develops an estimation technique to nowcast WBC data based on a coincident indicator of LPMS and unemployment data. Nowcasts are averaged across models with different sets of predictors. The results indicate that the LPMS and unemployment data provide valuable information in predicting contemporaneous WBC values, and that a model averaging approach to nowcasting waterborne commerce can substantially increase predictive performance. Benchmark priors provide a data-based method of sifting through and downweighing less relevant explanatory variables. The

BMA technique included all potential predictors in each commodity specific nowcast while maintaining sufficient degrees of freedom. Hence, BMA helped to alleviate the problems associated with an overparameterized model while also preserving statistical power. This approach provides a consistent way of incorporating both model and parameter uncertainty.

Historically, nowcasts of waterway traffic were impeded by issues of variable selection and changes in traffic patterns. BMA with MC^3 overcomes these issues by sampling the model space and constructing nowcasts that contain highly informative predictors. Individual locks that signal WBC flows are included in producing nowcasts, while excluding locks that contain too much noise. Implementing the nowcast with a rolling window helps to incorporate issues arising from changes in traffic patterns. Leveraging the LPMS and unemployment data to predict contemporaneous and future WBC values provide both market participants and government policy makers useful information earlier than if they wait for the release of the actual data.

The BMA approach is limited by computational resources and the quality of available data. Market participants and government policy makers interested in quantifying model uncertainty, without prior knowledge of the predictive ability of their covariates, can set benchmark priors and let the data drive the results. This approach can be generalized to wide data sets $(N < K)$ that lack the statistical power necessary to conduct valid inference. Future areas of application may include long-run forecasts of transport demand, where the periodicity and structure of the data tend to dictate the set of feasible and appropriate estimation techniques.

CHAPTER III
A MULTIPRODUCT COST FUNCTION FOR RAILROADS AND THE CURSE OF DIMENSIONALITY

III.1 Introduction

Railroads are a network technology that produce an enormous number of outputs. For regulatory purposes and for making informed decisions, there is a need for origin-destination-commodity specific measures of cost. Further, the reflection of multiple outputs is necessary to properly estimate the incremental cost of a shipment, the degree of scale and scope economies. Most of the previous literature has handled these problems by aggregating outputs and including aggregate descriptions of the railway network (Chiang and Friedlaender, 1984; Harmatuck, 1981). However, the appropriate measure of output remains a leading issue in transport economics (National Academies of Sciences, 2015).

In this paper, I develop and estimate a quadratic cost function for estimating shipment specific rail costs. The primary contribution of this research is estimating multiproduct cost functions that allow regulators and market participants to measure the costs associated with specific shipments. This technique has several additional advantages relative to the current regulatory approach. Estimating this cost function allows for the analysis of economies of scale and scope, an important feature that policy-makers should consider when designing railroad regulations. Furthermore, the cost function is estimated using only first and second moments of shipment and railway characteristics, a sizeable reduction in the data needed to estimate shipment specific costs. This is a novel application of the quadratic cost function to railway networks.[1]

Transportation is a vital service impacting virtually all economic activities. In the context of railroads, these networks played an important role in the rapid expansion and development of the U.S. economy, as they helped facilitate the growth of other sectors such as agriculture and energy production (Brown, 2013). However, there are features inherent in railroad production and costs that result in highly concentrated markets. Large fixed factor investments and the spatial nature of the railroad industry exacerbate concentration and result in high degrees of market power.[2] These features also contribute to railroads experiencing scale economies (Caves et al., 1981; Friedlaender and Spady, 1981; McKenzie and Wilson, 2016). There is theoretical justification for regulators to take an active role in industries with scale economies and market power (Baumol et al., 1983; Keeler, 1983). Regulators are tasked with balancing the harm caused by market power with the efficiency gains from large railroads (Boyer, 1977; Schmalensee and Wilson, 2016).

As the first industry in the U.S. to be federally regulated, the structure of the railroad industry has gone through significant regulatory reform. Historically, rail rate regulation has been a balancing act between protecting shippers from unreasonable markups associated with geographic market power while also ensuring revenue adequacy for the railroads so that they may attract sufficient capital to ensure long-term sustainability of the transportation network (National Academies of Sciences, 2015). In the early 1900s, the railroad industry faced little competition and the industry thrived. However, new and competing forms of transportation such as barges and trucks decreased demand for rail services and threatened the financial viability

[1] An intractable option is to estimate the model in the output (rather than the shipment characteristic) space.

[2] I present a map of the current U.S. rail network in the Appendix Figure A.III.1.

of the rail industry. With strict regulations in place, the railroad industry was slow to adapt to these competing forms of transportation. As a result, there were high profile bankruptcies in the 1970s that forced regulators to rethink their approach to regulation. Partial-deregulation of the industry began with the Revitalization and Regulatory Reform (4-R) Act of 1976 and the Staggers Act of 1980. This movement towards deregulation gave railroads more freedom in pricing. Deregulation also resulted in industry consolidation with more shippers having fewer shipping options (Keeler, 1983). Although the financial viability of the railroads had improved, there were again concerns of excessive shipping rates (Bitzan and Wilson, 2007).

In order to assess the competitiveness of the railroad industry and the reasonableness of rates, regulators must have accurate measures of railroad cost. Rail costing (i.e. the costing of a specific movement) is an issue that has been studied extensively for over a century (Lorenz, 1916; Clark, 1925). Since its inception, estimating railroad cost functions has diverged along two distinct paths. While academic economists typically model aggregate cost functions to analyze economies of scale, scope, and cost subadditivity, regulators are more interested in measuring the costs of specific rail movements. The most recent studies estimate costs of specific shipments; however, the literature lacks consensus on the proper definition of output. Railroads operate over differentiated networks, where they ship various products for various shippers. The spatial nature of the railroad industry and data limitations have prevented an econometrically tractible model of a multiproduct railroad.

Current rail regulation in the US relies on the Uniform Rail Costing System (URCS) to estimate the cost of a shipment.[3] Specifically, jurisdiction to consider the reasonableness of a rate requires that the revenue exceed variable cost by at least 180% and that the regulator finds that the traffic is market dominant. Regulators use URCS to measure costs; however, URCS is only capable of providing an accounting

[3]URCS documentation can be found at the following website
`https://www.stb.gov/stb/docs/URCS/URCS%20User%20Manual.pdf`

measure of costs, called "variable cost".[4] Additionally, URCS requires an enormous amount of data to develop its measure of "variable cost" (ICC, 2016). The Surface Transportation Board (STB) uses URCS to compute the "variable cost" of a shipment, and uses the shipment level revenue-to-variable cost ratio as an initial screen to assess market dominance over shipments. Thus, having an accurate representation of shipment level costs is important for regulatory purposes. Possible amendments to URCS have been proposed throughout the last several decades; however, the large number of product-origin-destination combinations has precluded regulators from estimating an econometrically tractible model of shipment specific costs, with recent work calling for the abandonment of URCS (Wilson and Wolak, 2016).

The remainder of the paper proceeds as follows. Section 2 provides a brief overview of the history of the railroad industry and rail regulation in the US. Section 3 reviews the literature on cost functions, particularly as they apply to modeling the railroad industry. Section 4 provides a theory of quadratic cost functions. In Section 5, I discuss the data sources in greater depth, the process to assemble the data set, and some summary statistics. I present the results of the empirical estimation in Section 6. Finally, Section 7 provides some discussion and concluding remarks.

III.2 Background

This section provides background of the U.S. railroad industry, its regulation and partial deregulation, and how the industry has responded to these regulatory changes. The first subsection describes the inception of the industry and the impetus for regulation. The second subsection describes rail industry deregulation and the current rail costing approach. The third subsection describes how rail costing assists regulators in enforcing rail regulations.

[4]Note that the Interstate Commerce Commission measure of "variable cost" is a weighted average of total costs from individual railroad cost categories, whereas the economic definition of variable cost is a cost that varies with the level of output.

III.2.1 Railroads and Regulation

As one of the nation's oldest industries, railroads have played an important role in the U.S. economy. In the beginning, rail transportation faced little competition, as it was faster, more comfortable, and the only option for traveling long distances in a reasonable amount of time (Brown, 2013). As a result, railroads were successful and the industry flourished. Railroad expansion led to the economic growth and development of other industries such as agriculture and energy production. As the economy expanded, so too did the demand for rail services.

The railroad industry has several features associated with natural monopoly and market power. Railroads were privately owned and operated over differentiated networks, which contributed to varying degrees of geographic market concentration, especially on a local level (MacDonald and Cavalluzzo, 1996). Additionally, constructing rail networks require railroads to incur large sunk capital investments. However, decades of competitive behavior in the railroad industry resulted in too many overlapping rail networks, which threatened the profitability and long-term viability of the railroad industry. The railroads realized that they could offer services at a lower cost through cooperating and consolidating. This consolidation exacerbated local market concentration, which in turn gave railroads tremendous market power. As market power increased, so too did concerns of excessive rates. Railroads began offering bulk discounts to large corporations; however, small shippers such as farmers and small businesses were unable to qualify for these discounts and faced high shipping rates (Miller, 1954). As a result, many small shippers were unable to compete with large corporations while remaining profitable. This led to protests from small businesses and farmers, which gathered sufficient political support to warrant government intervention. The government recognized the need for regulations that balanced efficiency gains from natural monopoly along with the social harm from excessive rates and discriminatory pricing.

Federal railroad regulation began with the Interstate Commerce Act (ICA) of 1887, making railroads the first industry subject to federal regulation. The ICA sought to outlaw discriminatory rate-setting and establish a common carrier obligation to service specific rail routes. To accomplish its goal, the ICA established the Interstate Commerce Commission (ICC), an agency charged with regulating the transportation of goods and services between states. The ICC provided regulatory oversight of railroads in terms of minimum and maximum rates, merger activity, and punishment of collusive behavior (Keeler, 1983). Unfortunately for the ICC, determining which rates were discriminatory proved to be outside the the scope of the ICA.

Rail costing became a priority for the ICC. Established in 1939, Rail Form A (RFA) became the workhorse costing methodology for the ICC. RFA takes an accounting-based approach to explain the costs of performing various railroad activities, including track maintenance, freight car repairs, and road train inspection. Although RFA helped establish a consistent approach to allocating rail costs, the declining financial health of the rail industry post World War II along with several high profile railroad bankruptcies of the 1970's exposed the need for more rail rate flexibility. That is, if the industry were to survive and attract the capital necessary to sustain the rail network, then rates would need to be adjusted in order to protect profits.

III.2.2 Partial Deregulation and Its Effect on the Industry

The financial ruin of several large railroads in the 1970s highlighted the need for more freedom in operational decisions. Additionally, new competing forms of transportation such as barges, trucks, and airplanes reduced the market power of railroads. As demand for rail transportation fell, it became clear that the stability of the industry relied heavily on giving railroads more freedom and removing regulations. Railroad deregulation began with the Railroad Revitalization and Regulatory Reform (4-R) Act of 1976, which reduced price regulations and gave firms more control over entry and exit decisions. Deregulation continued with the Staggers Rail Act of 1980, which relaxed constraints on the rates railroads can charge, the lines over which they can operate, on merger activity, as well as a wide array of other activities. Deregulation impacted the industry by substantially reducing the level of inefficiency in the market, increasing productivity which resulted in substantial declines in railroad costs and prices (Wilson and Burton, 1994; Bitzan, 2003). Another important feature of the Staggers Rail Act is its annual revenue adequacy check, a direct response to the high profile railroad failures of the 1970s. These checks were designed to ensure the railroads, "achieve a rate of return sufficient to attract the capital necessary for long-term financial viability" (National Academies of Sciences, 2015). Some regulations remained in place, however, such as protecting rail shippers from excessive rates and from loss of service in markets that lacked alternative transportation options. Overall, the Staggers Rail Act led to lower rates and lower costs of services.

Although Staggers successfully reduced both costs and rates, this partially deregulated market required accurate measures of rail costs. Tasked with both ensuring rate reasonableness and railroad revenue adequacy, the ICC looked to improve upon its rail costing method of RFA. Adopted in 1989 as the ICC general costing program, URCS makes a practical and transparent attempt at estimating the costs of individual railroad movements (Bitzan and Wilson, 2003). Designed to "protect shippers from excessively high rates, to ensure revenue adequecy of the railroads, as well as the long-term financial viability of the industry" (STB, 2016b), URCS takes an accounting based approach to estimating the "variable cost" of a generic type of shipment. Based on a vector of observable shipment characteristics, URCS's accounting-based approach allocates railroad costs to a generic shipment type.[5] That is, instead of

[5]URCS also helps to make cost determinations in abandonment proceedings; to provide a standardized costing model to market participants; and to cost the STB Car Load Waybill Sample.

estimating a cost function, URCS relies on railroad activity information to estimate unit cost factors (STB, 2016a). Railroads report operating expenses and traffic data directly to the STB. The STB then annually assembles a database that is used to estimate variable and total unit costs for US Class I railroads. URCS constructs a measure of "variable cost" by creating a weighted average of railroad cost activities such as track maintenance, freight car repairs, and road train inspection. Costs are regressed on capacity measures (i.e. track miles) and output measures (i.e. train miles) via OLS. This linear model assumes that capacity measures are fixed and output measures are variable. The resulting estimates are used to construct the "variable cost" of specific shipments by measuring "the amount of output associated with specific shipments (train miles) and their corresponding impacts on various activity expenses" (Bitzan and Wilson, 2007).

To better understand URCS, I detail its accounting cost allocation procedure. Following the notation of Rhodes and Westbrook (1986), the URCS "variable cost" function is represented by:

$$VC = R(q;1)C(q;1) + R(q;2)C(q;2) + ... + R(q;K)C(q;K) \tag{III.1}$$

where R is the variability ratio, C is the cost function for the k^{th} cost category, and q is railroad output. The cost function itself is composed of fixed costs (F) and variable costs (V):

$$C(q;k) = F(k) + V(q;k) \tag{III.2}$$

Within each cost category, the variability ratio represents the portion of total cost that varies with output:

$$R(q;k) = \frac{V(q;k)}{F(k) + V(q;k)} \tag{III.3}$$

The URCS accounting based approach proceeds by establishing the variability ratio. To accomplish this task, regulators estimate a linear cost function of the k^{th} cost category:

$$C(k) = \alpha S + \sum_m \beta_m q_m \tag{III.4}$$

where α and β are parameters to be estimated, S is a measure of fixed capacity, and q_m are individual output measures. Estimating the cost function in this way allows for αS to represent fixed costs of the k^{th} category and $\sum_m \beta_m q_m$ to represent variable costs. The corresponding estimates from equation III.4 help to form the variability ratio:

$$R(k) = \frac{\sum_m \beta_m q_m}{\alpha S + \sum_m \beta_m q_m} \tag{III.5}$$

Individual output variability ratios are then established by:

$$R(k, m) = \frac{\beta_m q_m}{\alpha S + \sum_m \beta_m q_m} \tag{III.6}$$

III.2.3 Market Dominance

The 4-R Act and Staggers Act were designed to protect shippers that face excessive rates and that do not have an economically viable alternative for a shipment. To accomplish this task, regulators assess whether the movement is "market dominant". Currently, market dominance is defined as the absence of effective competition from other railroads or modes of transportation and that the rate exceeds 180% of the URCS "variable cost" (49 USC 10707). The STB can consider the reasonableness of a rate only if the railroad is market dominant over the movement. A rate is automatically considered reasonable if the revenue the railroad receives does not exceed 180% of the URCS "variable cost". If this occurs, then the rate in question is not rebuttable by a shipper. However, if a rate is more than 180% of its "variable cost" and is in a market lacking effective competition, then the shipper can challenge the rate by providing evidence to the STB. Shippers should provide evidence that shows a lack of effective competitive in the market. Next, the STB conducts its own analysis to determine market dominance. If the STB finds the railroad to be market dominant over the movement, then reasonableness of the rate may be considered.

Reasonableness of a rate may be considered under three different methods including the Stand-Alone Cost (SAC) standard, the Simplified SAC, and the Three Benchmark test. The SAC test measures the lowest cost at which a hypothetical, efficient carrier could provide the service. The total cost of the hypothetical railroad helps determine establish an upper bound on the rate that is deemed reasonable for the shipment, which includes an adequate return on invement. Several commentators have argued against the use of the SAC test, as the assumptions of the method do not reflect reality (Pittman, 2010). Faulhaber (2005) notes, "the use of Stand-Alone Cost in railway rate regulation is so far from the models in which it was originally developed as to be unrecognizable." There are practical challenges with this approach as well. Furthermore, this approach is both expensive and time-consuming, with STB estimating the costs of pursuing a SAC case often exceed $5 million.[6] The regulatory burden for SAC rate cases in terms of cost and complexity necessitated an expedited procedure for resolving rate disputes. Under the Simplified SAC, consideration is given to the replacement cost of rail network infrastructure used to provide service including the return on investment to replicate the infrastructure. These costs are then used to determine a reasonable rate. The Three Benchmark test helps shippers with smaller claims by substantially reducing the cost and evidentiary burden incurred from the SAC and Simplified SAC methods. This approach determines the reasonableness of the rate by comparing it to three rate benchmarks. The benchmarks

[6]STB Ex Parte No. 715, Rate Regulation Reforms, July 8, 2013, pp. 10-11.

incorporate the revenue of a shipment along with URCS "variable cost". If the STB considers the rate to be unreasonable, then the railroad must compensate the shipper for overpayments, and it may recommend the maximum tariff rate the railroad can charge for future movements (49 USC 11704(b), 10704(a)(1)).

URCS helps regulators screen shipments and assess the reasonableness of a rate. As these methods of determining reasonableness of a rate depend on "variable cost", URCS must provide an economically meaningful measure of shipment-level costs. Although URCS improves upon the previous rail costing methodology of RFA, the STB Railroad-Shipper-Transportation Advisory Council believes that URCS is an "outdated and inadequate costing system" that does not meet the law's requirement for economically accurate shipments costs (STB, 2011). Specifically, URCS is unable to provide a cost measure that a profit-maximizing railroad would use to make operating decisions. Wilson and Wolak (2016) provide evidence that the URCS "variable cost" can differ significantly from the increase in the railroad's total cost of moving the shipment. They present empirical evidence to support the conclusion that URCS is inconsistent with firm profit maximization. For example, in 2010, over 23% of partially-deregulated rail rates were *less than* "variable costs".

III.3 Literature Review

This section highlights existing literature related to modeling operations of the firm and how these models have been applied to analyze the structure and competition of the railroad industry. The first subsection briefly describes the evolution of econometric models of cost. The second subsection focuses on how these costing methodologies have been used to evaluate the structure of the railroad industry.

III.3.1 Cost Functions

Empirical industrial organization economics estimates firms' cost functions to analyze industry competition. Econometric techniques have been developed to help account for issues with data and specification, and as these methods have evolved, so to has our understanding of how firms make operational decisions (Schmalensee, 2012). Estimating cost functions econometrically allow for estimates of marginal costs, efficiency levels, and scale elasticities. Estimation proceeds based on an assumption that firms operate in a way that transforms inputs into outputs such that the firm minimizes cost.

A traditional way of estimating costs starts by assuming a production function that maps factors of production into physical output. The Cobb-Douglas production function takes a functional form that is relatively easy to estimate econometrically (Cobb and Douglas, 1928). However, a drawback of this approach is that it implies the elasticity of substitution between any two inputs is always one. Econometric modeling of cost functions progressed with the introduction of the transcendental logarithmic (translog) function (Christensen et al., 1973). Advantages of the translog function follow from its flexibility and relatively few restrictions it places on the production structure of the firm. That is, the translog function approach can incorporate a flexible form for the elasticity of substitution between inputs. The New Empirical Industrial Organization (NEIO) model is useful in establishing an econometric model of an industry (Bresnahan, 1981). The NEIO approach estimates marginal costs and markups in specific industries by establishing a system of equations for demand, costs, and pricing. Based on the standard profit maximization condition of equating marginal revenue to marginal cost, this model estimates relavent cost parameters through prices.

Quadratic cost functions provide a functional form that help account for non-linearities in the factors of production. Suggested by Baumol et al. (1983), Spady (1986) extends this approach by indexing individual production units. The quadratic cost function has a convenient aggregation property that helps facilitate its estimating econometrically. Specifically, this technique can be used to overcome issues of dimensionality by modeling aggregate costs with first and second moments of production units. The quadratic cost function is parsimonious in parameters and is fully as flexible as the translog. Spady notes that these functions are capable modeling multiproduct network technologies; however, this approach has yet to be applied to transport industries.

III.3.2 Rail Costing

Estimating cost functions is an issue that has been studied extensively throughout the transport economic literature. In the context of railroads, these cost functions play a vital role in assisting regulators with assessing the reasonableness of a rate. They can be used to compare costs of transporting a good amongst various modes of transport, as well as generating estimates of productivity growth that help to evaluate performance of an industry throughout time. This section summarizes the pivotal methods that have contributed to rail costing for transport networks.[7]

The widespread availability of data in transportation has helped facilitate the analysis of the railroad industry (Walters, 1963). Lorenz (1916) and Clark (1925) were the earliest contributors to the rail costing literature. These early contributions to the transport economics literature focused on normative issues such as optimal rates for railroads and whether and how to regulate carriers' operations. There is a long history of empirical work in transport economics; however, many issues that were raised are still of concern today (Winston, 1985). Simple cost models focus on a single output (Harris, 1977). However, these models are unable to incorporate a

[7]See Bitzan and Wilson (2007) Table B.1 for a more detailed timeline of advances in rail costing techniques.

realistic representation of the operational decision-making of railroads, and are thus ineffective in policy analysis. With an enormous number of origin-destination-product combinations, the field has struggled to find an appropriate measure of output.

Modern rail costing progressed with the introduction of the translog function. Several studies have applied and refined this technique to modeling the railroad industry. First introduced to the transport literature by Spady and Friedlaender (1978), Chiang and Friedlaender (1985) extend the single generic output to multiple generic outputs in the motor carrier industry. Bitzan and Wilson (2007) incorporate product heterogeneity via a hedonic translog cost function to model rates in the railroad industry. Their results are lower than the costs generated by URCS, and in some cases, the difference in per unit costs are high. However, they find that the translog cost function does not perform well for individual shipment costing. Caves et al. (1981) also use a translog approach to incorporate the multi-product nature of railroad output. These approaches to modeling costs of a multi-product firm are useful for policy analysis; however, they are only tractible econometrically for small transport networks, as larger networks face the familiar issue of dimensionality.

Wilson and Wolak (2020) propose a benchmarking approach to identifying potentially non-competitive rates that are in excess of rates expected in competitive markets. Importantly, this approach does not rely on knowledge of the firm's multiproduct cost function. Assuming competitive prices, they estimate a nonparametric model that estimates the conditional distribution of competitive prices given product characteristics. Next, they leverage this conditional distribution to construct a benchmark price, which itself is a function of observable characteristics of a shipment suspected of having an "excessive" price. Finally, they compare the benchmark price to the actual price to determine if the rates may require regulatory review. This is a considerable departure from traditional approaches.

III.4 Modeling Network Technologies

This section details the theory I use to model multiproduct cost functions. A critical issue in transportation economics is the appropriate measure of output. Specifically, commodity and shipment characteristics are so important to market definition that they must be accounted for explicitly in the model in order to understand the true nature of shared network technologies. To accomplish this goal, I adapt and apply a quadratic function to estimate the multiproduct cost function for shipment specific costs (Baumol et al., 1983). Constructing the cost function as quadratic functions of outputs allows me to treat the resulting coefficients as concave independent homogeneous functions of input prices. The contribution of this approach is that I rely on first and second moments of shipment and railway characteristics.

III.4.1 Quadratic Functions

Below I detail the indexed quadratic function capable of modeling the cost for shared network technologies. Following the notation of Spady (1986), the firm can view its costs of producing vector output y at factor prices p under technological conditions t; denoting (y, t) by z:

$$c = \alpha_0 h_0(p) + \sum_k \alpha_k h_k(p) z_k + \sum_k \sum_m \beta_{km} \phi_{km}(p) z_k z_m \tag{III.7}$$

Suppose there are s shipments and there exists a price index $h(p)$ that is common to all factor of production, then III.7 can be rewritten as:

$$c = \alpha_0 h(p) + \sum_k \alpha_k h(p) z_k + \sum_k \sum_m \beta_{km} h(p) z_k z_m \tag{III.8}$$

The most convenient attribute of the quadratic cost function resides in its aggregation property. Denote the z and c of the i^{th} shipment by z^i and c^i, and the mean of z by $\bar{z}$. Defining $\epsilon^i = z^i - \bar{z}$ allows III.8 to be written as:

$$c^i = \alpha_0 h(p) + \sum_k \alpha_k h(p)(\bar{z}_k + \epsilon^i_k) + \sum_k \sum_m \beta_{km} h(p)(\bar{z}_k + \epsilon^i_k)(\bar{z}_m + \epsilon^i_m) \quad \text{(III.9)}$$

Summing III.9 over the s shipments yields:

$$C = \sum_s c^i \quad \text{(III.10)}$$

$$= h(p)s \left[\alpha_0 + \sum_k \alpha_k \bar{z}_k + \sum_k \sum_m \beta_{km}(\bar{z}_k \bar{z}_m + \sigma_{km}) \right] \quad \text{(III.11)}$$

where $\sigma_{km} = \frac{1}{s} \sum_s \epsilon^i_k \epsilon^i_m$ represents the covariance of z_k and z_m. Thus, the number of units and the means and variances of the outputs and characteristics provide an exact representation of the aggregate technology (Spady, 1986). This is a sizeable reduction in the data gathering process relative to current regulatory standards.

Recall the goal of this approach is to estimate shipment specific costs. Marginal (shipment specific) costs of the i^{th} output of the railway network is accomplished by differentiating with respect to z_i:

$$\frac{\partial \bar{c}}{\partial z_i} = \frac{\partial}{z_i} \left[\alpha_0 + \sum_k \alpha_k \bar{z}_k + \sum_k \sum_m \beta_{km} [\bar{z}_k \bar{z}_m + \sigma_{km}] \right] \quad \text{(III.12)}$$

That is, III.12 allows for an estimate of the incremental costs of an additional output unit in a way that both incorporates the shared technology of the rail network and keeps the model tractible econometrically. Evaluating III.12 at the output values of observed shipments results in a measure of shipment specific costs.

III.5 Data

The primary sources of the data are the Surface Transportation Board (STB) confidential Annual Carload Waybill Sample and the R-1 Annual Report of Finances and Operations. The waybill sample is a stratified random sample which represents at least 2.5% of all shipments each year. Each observation from the waybill sample is weighted by its sampling probability to account for the stratified sampling procedure. In addition, I use the R-1 to supplement the waybill sample with financial and operating information for Class 1 railroads. To account for changes in factor prices, I use the STB's productivity-adjusted Railroad Cost Adjustment Factor (RCAF-A) index, which provides a convenient price index of changes in the price of major railroad operating costs. These operating inputs include labor, fuel, materials, equipments rents, and interest on debt (National Academies of Sciences, 2015). These data cover all Class 1 railroads over the 2000 through 2016 period.

Due to substantial merger activity in the 1980's and 90's, I focus on data beginning in year 2000. Throughout the sample, there are 119 firm years. The seven Class 1 railroads are comprised of BNSF Railway Co., CSX Transportation, Grand Trunk Corporation[8], Kansas City Southern Railway, Norfolk Southern, Soo Line Corporation[9], and Union Pacific Railroad. In 2016, these seven railroads accounted for 68% of US freight rail mileage, 88% of employees, and 94% of revenue (JOC, 2016). In developing the model, I use total annual cost per shipment as the dependent variable. This variable, and all other cost variables, are defined in Table III.1. Based on these self-reported figures, I follow the literature (Bitzan and Wilson, 2007) and construct an annual measure of total cost for each of the seven Class 1 railroads:

$$C = OpCost - CapExp + RoiRd + RoiLcm + RoiCrs \tag{III.13}$$

[8]Canadian National's operations

[9]Canadian Pacific's operations.

where C is total annual cost, $OpCost$ is operating cost, $CapExp$ is capital expenditure, $RoiRd$ is return on investment in road, $RoiLcm$ is return on investment in locomotives, and $RoiCrs$ is the return on investment in cars.[10]

Table III.1
Cost Variables

Variable	Definition	Source
C	Total cost	R1
s	Number of shipments	Waybill sample
$\bar{c}$	Real total cost per shipment	R1, Waybill
d	Distance (miles)	Waybill sample
t	Tonnage	Waybill sample
u	Unit train	Waybill sample
$CarType$	Type of rail car	Waybill sample
$h(p)$	Roadroad cost adjustment factor	AAR Railroad Facts
$OpCost$	Railroad operating cost	R1, Sched. 410, ln. 620, Col F
$CapExp$	Capital expenditures	R1, Sched. 410, ln. 12-30, 101-109, col. F
$RoiRd$	Return on investment in road	$(RoadInv - AccDepr) * CostK$
$RoadInv$	Road investment + $CapExp$ (cumulative)	R1, Sched. 352B, ln. 31, col. B
$AccDepr$	Accumulated depreciation in Road	R1, Sched. 335, ln. 30, col. G
$CostK$	Cost of capital	AAR *Railroad Facts*
$RoiLcm$	Return on investment in locomotives	$[(IboLoco + LocInvl) -$ $(AcdoLoco + LocAcdl)] * CostK$
$IboLoco$	Investment base in owned loc.	R1, Sched. 415, ln. 5, col. G
$LocInvl$	Investment base in leased loc.	R1, Sched. 415, ln. 5, col. H
$AcdoLoco$	Accum. depr. owned loc.	R1, Sched. 415, ln. 5, col. I
$LocAcdl$	Accum. depr. leased loc.	R1, Sched. 415, ln. 5, col. J
$RoiCrs$	Return on investment in cars	$[(IboCars + CarInvl) -$ $(AcdoCars + CarAcdl)] * CostK$
$IboCars$	Investment base in owned cars	R1, Sched. 415, ln. 24, col. G
$CarInvl$	Investment base in leased cars	R1, Sched. 415, ln. 24, col. H
$AcdoCars$	Accum. depr. owned cars	R1, Sched. 415, ln. 24, col. I
$CarAcdl$	Accum. depr. leased loc.	R1, Sched. 415, ln. 24, col. J

Note: All R-1 variables available at the annual level. All Waybill variables are aggregated to the annual level, from data available at the daily level.

The R-1 allows me to analyze firm-year components of cost. The R-1 report is the result of railroads reporting to the Interstate Commerce Commission (ICC) and the Surface Transportation Board (STB) and is available for all railroads and all years of the sample. In Table III.2, I present firm-year averages from the R-1 data.[11] Cost, miles of road, and total road investment are highly correlated, suggesting that

[10]While Bitzan and Wilson (2007) construct total cost, I deviate and construct total cost per shipment to allow for the estimation of a quadratic cost function.

[11]These results are displayed in more detail in the Appendix Figure A.III.2.

the size of the rail network and the corresponding track maintenance influences firm cost. This is in line with the literature (Bitzan and Wilson, 2007), as each firm is responsible for operating and maintaining their portion of the rail network, which varies in size.

Table III.2
R-1 Firm-Year Averages

Railroad	Cost (C)	Miles of road	Road Investment	Revenue Ton-Miles
BNSF	16,267	32,393	39,830	604,529
CSX	10,473	21,588	24,877	232,176
GTC	2,672	6,013	9,184	52,326
KCS	1,035	3,151	3,012	27,194
NS	9,767	20,698	23,897	19,088
SOO	1,059	4,258	2,762	2,848
UP	16,958	32,351	44,005	522,941

Note: Cost in millions, Road Investment in millions, Revenue Ton-Miles in millions.

Next, I turn to the waybill sample for shipment variables that contribute to costs. These can be classified as operating and/or network variables. The shipment variables include *Shipments*, *Distance*, *Tons*, and *Unit*. *Shipments* is the total number of shipments for each railroad in a given year. *Distance* is defined as the actual distance traveled (in miles) by all carriers in the route, calculated by RAILINC's Princeton Transportation Network Model. *Tons* is billed weight in tons. *Unit* is defined as a shipment with 50 or more cars. Recall that the waybill data is a stratified sample where the sampling probabilities increase as the number of carloads in a shipment increase. The waybill sample contains an expansion factor for each commodity that allows me to expand the stratified sample to represent the population of shipments.[12]

From the sample of rail shipments, I construct firm-year averages of each variable. These are the variables used in the forthcoming estimation, such as average tons ($\bar{t}$), average distance ($\bar{d}$), and average unit train ($\bar{u}$). Additionally, I use the firm-year cost from the R-1 and firm-year shipments to construct cost per shipment. Total costs are

[12] Wolfe (2004) provides a more complete description of the waybill data.

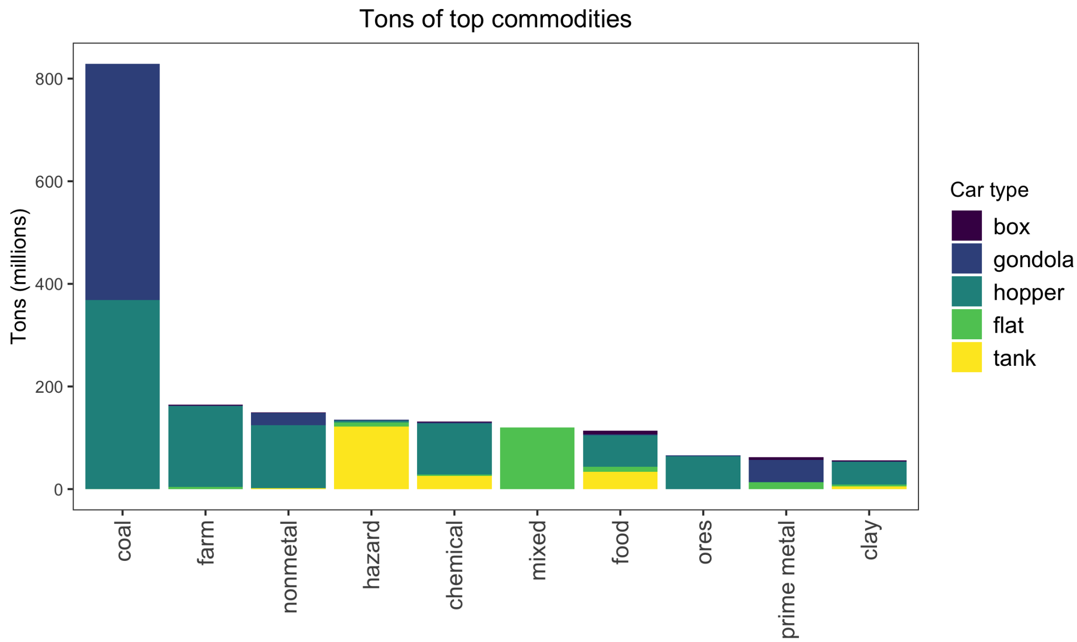
likely increasing in shipments, as more shipments result in the use of more factors, such as fuel, labor, and capital. Cost per shipment is likely increasing in distance, tons, and unit train. Traveling farther distances requires more fuel, labor, and track maintenance. Carrying more tons requires more durable car types. Increasing the number of cars in a shipment increases rail costs as well. More active railroads such as BNSF and UP tend to travel farther distances. Less active railroads such as GTC and KCS tend to carry heavier shipments.

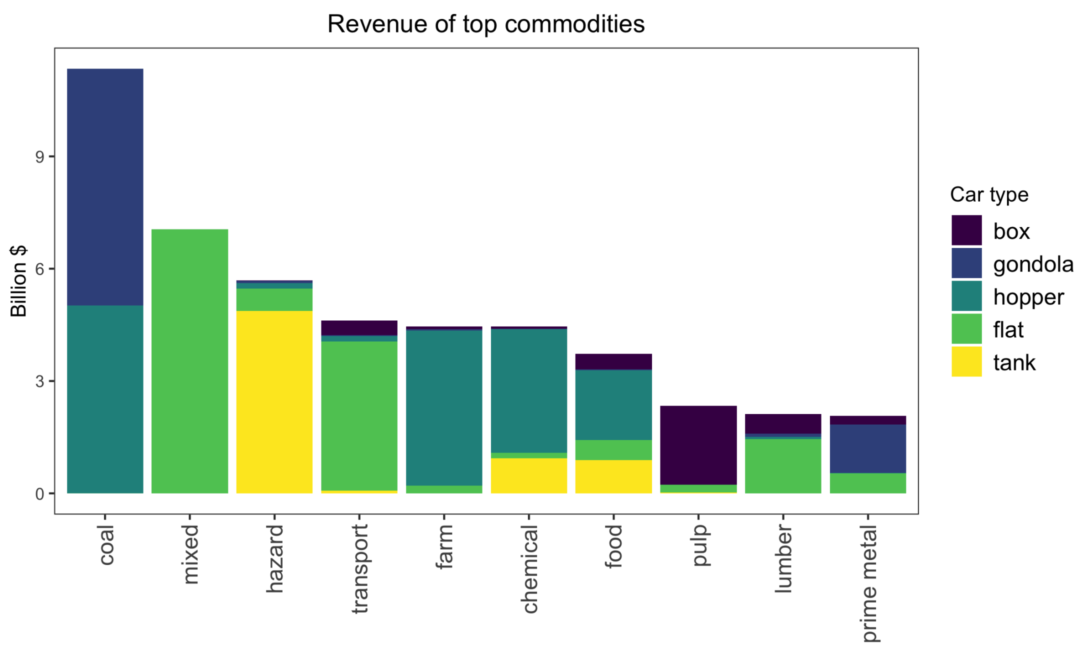
Finally, I incorporate the multiproduct feature of the cost function. Due to nassively multiproduct nature of railroads and corresponding issues of dimensionality, I am unable to include controls for each origin-destination-commodity combination. To address this issue, I construct measures of rail car type. That is, I group each shipment into one of five car type categories: box cars, gondola cars, hopper cars, flat cars, and tank cars. Doing so allows me to proxy for product type, while preserving statistical power. The relationship between commodity and car type is visualized in Figure III.1, where I present each commodity by car type. The first graphs displays the tons of each commodity by car type. The second graph displays revenue of each commodity by car type. Commodity and car type are highly correlated, as the major commodities tend to travel in predictable car types. This motivates the use of car type as a proxy for product type.

III.6 Results

In this section, I present the results for the quadratic cost function. As discussed earlier, the primary benefit of the quadratic cost function approach lies in its aggregation property. That is, I can recover the underlying disaggregate technology based on basically aggregate data. The variables described in the preceding paragraphs will now be used to estimate equation III.10. In this regard, I write the final model to be

Figure III.1
Commodity by Car Type





estimated in the following form:

$$\bar{c}_{jt} = \sum_k \alpha_k \bar{z}_{jt,k} + \sum_k \sum_m \beta_{km}[\bar{z}_{jt,k}\bar{z}_{jt,m} + \sigma_{jt,km}] + \kappa_{jt} + \phi_j + \lambda_t + \varepsilon_{jt} \qquad \text{(III.14)}$$

Where $\bar{c}_{it}$ is firm cost per shipment for firm i. Product and technological characteristics ($\bar{z}_k$) include average distance, average tons, average unit, and car type. Car type is defined as the percent of total shipments using the specific car type. Additionally, σ_{km} represents the covariance between product characteristics, such as average distance, average tons, and average junction frequency. Car type controls κ_{it} represent the percentage of shipments that use a specific car type within a given firm-year. Distance, tons, and junction frequency help control for product characteristics, while car type controls proxy for commodity. Firm fixed effects (ϕ_i) control for firm level differences that affect firm cost per shipment. Year fixed effects (λ_t) control for changes that affect profit in all markets.

Next, I display the empirical results for the quadratic cost function. Table III.3 provides estimates of several quadratic cost functions. Model (1) controls for average distance and average tons. In Model (2), I add in the control for average unit. Models (3) and (4) build on models (1) and (2) respectively, and add controls for car type. Across all specifications, average distance, average tons, and average unit are statistically significant and have an impact on cost per shipment. Additionally, car type does influence cost per shipment; however, these results are not robust across all car types. In order to evaluate the impact of each covariate on cost, these models must be evaluated at specific values, as the quadratic cost function is non-linear. I use model (4) as the preferred specification for the remainder of the analysis.

III.6.1 Marginal Cost Estimates

Estimating a quadratic cost function allows me to derive marginal costs. That is, I use model (4) presented in Table III.3 to measure the incremental cost associated with an additional unit of a specific commodity. Then, I use these average marginal effects to predict cost per shipment. Figure III.2 displays the predicted average cost by average distance and average tons. I allow the value of an individual shipment

Table III.3
Quadratic Cost Estimates

	$\bar{c}$			
	(1)	(2)	(3)	(4)
$\bar{d}$ (distance)	-55.66^{***}	-55.25^{***}	-47.06^{***}	-47.71^{***}
	(8.65)	(8.43)	(7.94)	(7.97)
$\bar{n}$ (tons)	-11.75^{***}	-16.45^{***}	-18.84^{***}	-21.69^{***}
	(3.69)	(4.46)	(3.74)	(4.47)
$\bar{u}$ (unit)			822,644.20	829,268.10
			(660,337.60)	(671,011.60)
$\bar{d} \cdot \bar{n}$	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
$\bar{d} \cdot \bar{u}$			251.46	143.57
			(479.82)	(516.16)
$\bar{n} \cdot \bar{u}$			$-1{,}615.22^{***}$	$-1{,}609.33^{***}$
			(420.98)	(433.66)
$\bar{d}^2$	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
$\bar{n}^2$	0.001	0.001	0.01^{***}	0.01^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
$\bar{u}^2$			$156{,}568{,}285.00^{**}$	$153{,}227{,}876.00^{**}$
			(60,964,790.00)	(61,186,869.00)
$\sigma_{\bar{n}\bar{d}}$	-0.0002	0.0000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma_{\bar{n}\bar{u}}$			24.24	33.86^{*}
			(17.45)	(18.56)
$\sigma_{\bar{d}\bar{u}}$			-284.04	-270.57
			(254.68)	(272.50)
Car controls?	No	Yes	No	Yes
Firm, Year FEs?	Yes	Yes	Yes	Yes
Observations	119	119	119	119
R^2	0.94	0.95	0.96	0.96

Notes: This table reports estimates of Equation III.14. An observation is a year. The dependent variable is cost per shipment. Annual fixed effects are included. Heteroskedastic robust standard errors in parentheses. Stars indicate p values: *p<0.1; **p<0.05; ***p<0.01.

characteristic to vary, and predict its impact on cost per shipment. Cost per shipment tends to increase with tons.

III.6.2 Quadratic Cost Function and URCS

This section compares the predictions of the quadratic cost function to those generated by URCS. For specific shipments, I use the quadratic results from Table III.3 to generate an estimate of costs. Then, I use the same shipment characteristics and rely on URCS for an estimate of costs. These results are displayed visually in Figure III.3, where I plot how the two rail costing approaches compare for identical shipments. The dashed 45 degree line allows me to compare URCS "variable cost" to the cost per shipment generated by the quadratic cost function. Notice that the majority of the quadratic cost function estimates shipment specific costs below those generated by URCS. For small shipments, the quadratic approach and URCS produce similar estimates of costs. However, as the value of the shipment increases, URCS cost tend to be higher relative to the quadratic cost function.

III.7 Conclusion

The railroad industry has experienced substantial regulatory reform. As new forms of transportation began competing directly with railroads, regulators have had to balance efficiency gains from natural monopoly along with the social harm from excessive rates and discriminatory pricing. In order to assess the reasonableness of a rate, regulators must have a method that captures the economic cost of moving a shipment. However, the current regulatory accounting approach of URCS has been heavily criticized.

This research estimates a model of railroad costs. I estimate the cost function using first and second moments of shipment and railway characteristics, which is a sizeable

Figure III.2
Marginal Cost Estimates

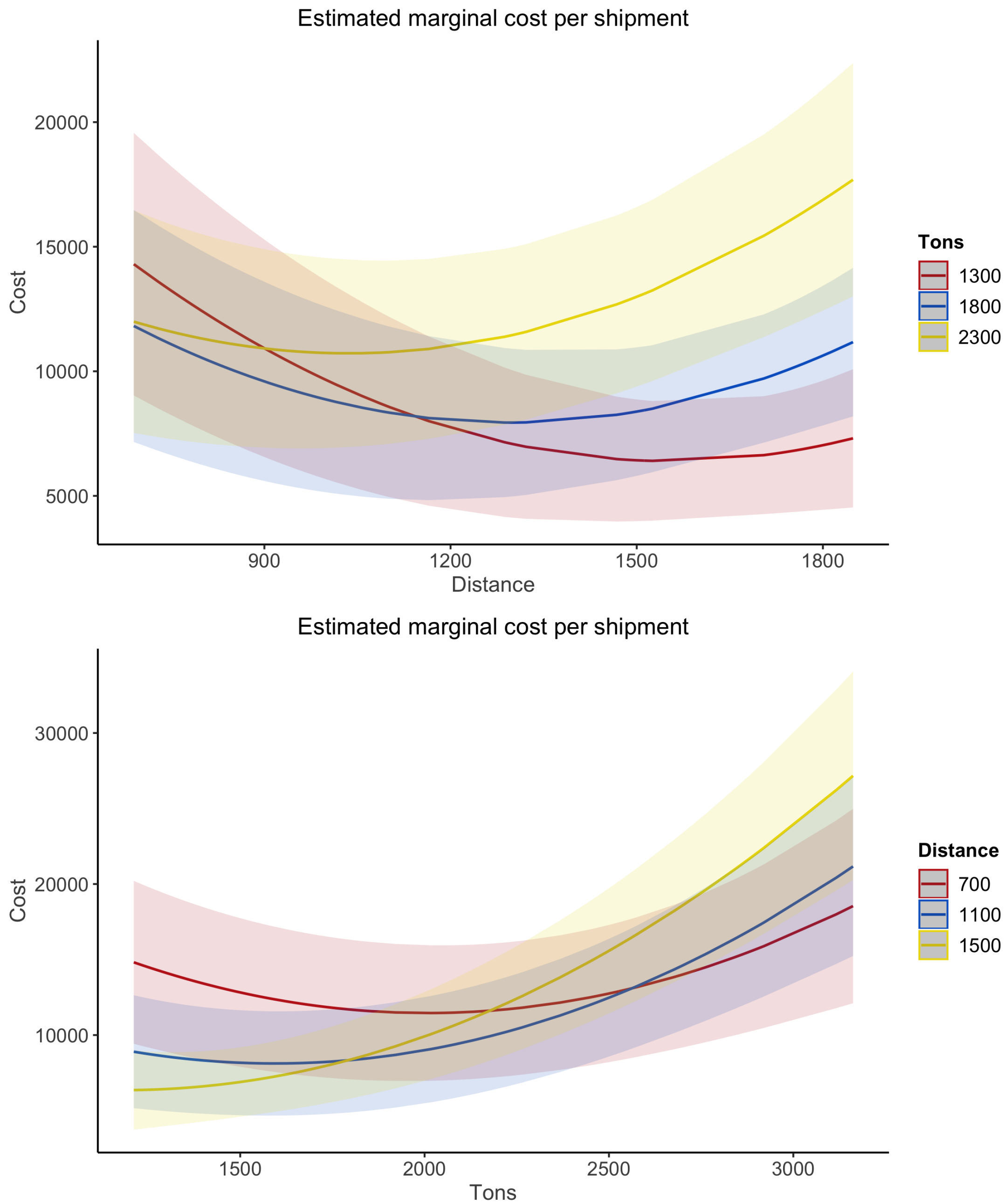
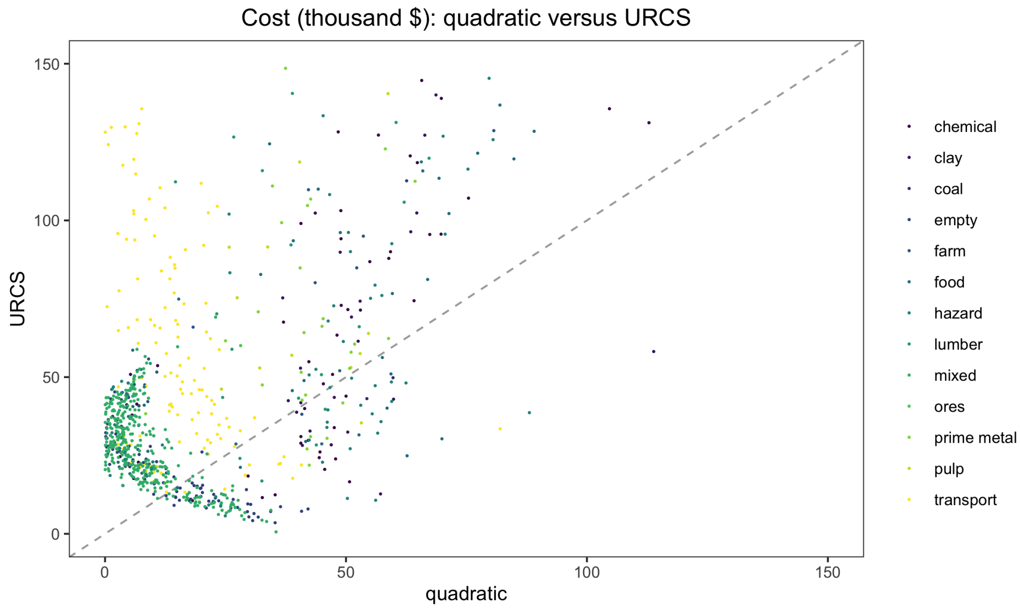


Figure III.3
Cost Comparison: Quadratic versus URCS



reduction in the data needed for regulatory analysis. The results from the quadratic cost function are used to predict costs for specific shipments, which allows me to directly compare shipment level costs to the current regulatory approach of URCS. I find that the quadratic cost function predicts costs below that URCS. Regulators can use this approach to screen for excessive rates, shippers can check to see if they may be eligible for rate relief, and railroads can operationalize this method to set competitive rates and avoid the dispute resolution process.

As regulators collect more financial information regarding the railroads, an increase in statistical power allows for the estimation of a more robust quadratic cost function. That is, one could add additional operating and network characteristics to the model while also ensuring it remains tractible econometrically. Alternatively, one could consider introducing measures for the congestion of adjacent links or nodes among the operating and network variables, which may play an important role in the cost function of network technologies. Armed with a consistent and reliable rail costing methodology, regulators could then explore economies of scale and scope. Additionally, a combination of accurate marginal cost estimates along with pricing data allows regulators to analyze the relationship between the transportation network and markups in rail rates. There remains important policy work within the rail costing literature.

CHAPTER IV

PRICES, COSTS, AND MARKUPS FOR DIFFERNTIATED RAIL NETWORKS

IV.1 Introduction

At the national level the U.S. railroad industry is heavily concentrated, with four companies controlling over 90% of the national rail freight movement. At the more local level, however, rail markets are even more heavily concentrated. Railroads serve a number of unique origins and destinations, carry many commodities, and generally operate independent tracks, which contribute to varying degrees of geographic market concentration, especially on a local level (MacDonald and Cavalluzzo, 1996). Indeed, 95% of origin-destination-commodity defined outputs in this study have but one railroad that provide direct service. Railroads price movements at the origin-destination-commodity-shipment type level and therefore the number of outputs and prices is astronomically large. Railroads are also subject to economic regulation, where regulators are tasked with protecting captive shippers from excessive rates while ensuring rates are sufficient for railroads to remain revenue adequate. Regulators need accurate measures of shipment costs to assess whether the rate is excessive, and if so, determine market dominance, defined as "an absence of effective competition from other rail carriers or modes of transportation for the transportation to which a rate applies" (STB Ex Parte No 756, 2019). However, the current approach to measuring shipment costs, markups, and determining market dominance is heavily criticized, as "methods for assessing rate reasonableness lack a sound economic rationale and are unusable by most shippers; sounder and more economical methods are needed" (National Academies of Sciences, 2015).

In this paper, I examine costs, markups, and market dominance in the railroad industry. In contrast to the academic literature, which is aggregate in nature and estimates the average cost and markup over the network, I develop a method to measure costs and markups in a way that retains their disaggregate properties. I adapt and apply a quadratic cost function theoretically developed by Spady (1986), but to my knowledge has not been empirically implemented. The result yields shipment costs and markups and I use these results to explore market dominance, wherein the markup and the presence of transport competition determine whether shippers may be eligible to contest the reasonableness of the rate. For each shipment, I construct measures of intermodal and intramodal competition and estimate markups as a function of these measures of competition. I find that a movement from monopoly to duopoly is associated with an average 6.8% decline in rail markups. The results suggest an interaction between intermodal and intramodal competition, where nearby ports decrease the impact of rail competition on rail markups. While current market dominance analysis relies on subjective testimony from an expert witness, my model provides an empirical analysis of how the presence of transport competition impact shipment markups. This approach can be operationalized by regulators and market participants to assess the reasonableness of a rate and to streamline and expedite market dominance inquiry.

Current rail regulations assess the reasonableness of a rate with an accounting cost allocation procedure, the Uniform Rail Costing System (URCS). URCS is a practical and transparent accounting procedure that provides the cost of a generic shipment; however, this approach has been heavily criticized. Regulators commissioned a study performed by Christensen Associates who found inconsistent revenue to variable cost ratios used for determining the reasonableness of a rate and recommended that "more appropriate measures of captivity should focus on the effects of the transportation market structure on rail rates, and by extension, markups" (Laurits R. Christensen Associates, 2009). More recently, the Transportation Research Board found the URCS cost allocations to be invalid and unrealiable (National Academies of Sciences, 2015). Although URCS provides accounting costs at a disaggregate level, it is "unable to provide a cost measure that a profit-maximizing railroad would use to make operating decisions" and should be abandoned (Wilson and Wolak, 2016). In contrast to the disaggregate accounting approach of URCS, there is a rich and long-lasting academic literature on railroad economic costs and markups. But these studies rely on highly aggregated measure of output and estimate the average cost over the rail network (Keeler, 1983; Chiang and Friedlaender, 1985; Bitzan and Wilson, 2003) or the average markup over the rail network (Ivaldi and McCullough, 2007; Coublucq, 2013; McKenzie and Wilson, 2016). To the best of my knowledge, there are few, if any, published studies that evaluate and consistently estimate the economic relationship between shipment costs, markups, and transport competition at a disaggregate level.

My research confronts these issues directly by modeling railroad operations with a multiproduct cost function that exploits the aggregation property of the quadratic model. The quadratic approach models economics costs using first and second moments of costs, product, and technological features in a way that retains their disaggregate properties. The results from the quadratic approach suggests shipment economic costs lower relative to URCS costs and disaggregate markups similar to previous studies of aggregate markups. I then use these shipment markups to quantify the relationship between markups and transport competition and find evidence of commodity heterogeneity. My model incorporates intramodal and intermodal competition and can be used in market dominance inquiry to streamline and expedite procedures.

The remainder of the paper proceeds as follows. Section 2 provides a brief overview of the history of the railroad industry and rail regulation in the US. Section 3 reviews the literature on costs and markups, particularly as they apply to modeling the railroad industry. Section 4 provides a theory of costs, markups, and market dominance. In Section 5, I discuss the data sources in greater depth, the process to assemble the data set, and some summary statistics. I present the results of the empirical estimation in Section 6. Finally, Section 7 provides some discussion and concluding remarks.

IV.2 Background

This section provides background of the U.S. railroad industry, its regulation and partial deregulation, and how the industry has responded to these regulatory changes. The first subsection describes the inception of the industry and the impetus for regulation. The second subsection describes rail industry deregulation and the current approach to measuring rail markups. The third subsection describes how rail markups assist regulators in enforcing rail regulations.

IV.2.1 Railroads and Regulation

Transportation is a vital service impacting virtually all economic activities. In the context of railroads, these networks played an important role in the rapid expansion and development of the U.S. economy, as they helped facilitate the growth of other sectors such as agriculture and energy production (Brown, 2013). In the beginning, rail transportation faced little competition, as it was faster, more comfortable, and the only option for traveling long distances in a reasonable amount of time (Brown, 2013). As a result, railroads were successful and the industry flourished.

However, there are features inherent in railroad operations that result in highly concentrated markets. Large fixed factor investments in conjunction with the geographic nature of the railroad industry exacerbate market concentration and result in high degrees of market power. This market power allowed railroads to engage in discriminatory pricing, offering bulk discounts to large corporations and charging high shipping rates to small shippers such as farmers and small businesses (Miller, 1954). Railroads also experience scale economies (Caves et al., 1981; Friedlaender and Spady, 1981; Wilson, 1997), and theory suggests regulators may improve market outcomes in industries with market power and scale economies (Faulhaber, 1975; Baumol et al., 1983; Keeler, 1983). Thus, regulators are tasked with balancing the harm caused by market power with the efficiency gains from natural monopoly (National Academies of Sciences, 2015; Schmalensee and Wilson, 2016; STB, 2019b).

Federal railroad regulation began with the Interstate Commerce Act (ICA) of 1887, making railroads the first industry subject to federal regulation. The ICA sought to outlaw discriminatory rate-setting and establish a common carrier obligation to service specific rail routes. To accomplish its goal, the ICA established the Interstate Commerce Commission (ICC), an agency charged with regulating the transportation of goods and services between states. The ICC provided regulatory oversight of railroads in terms of minimum and maximum rates, merger activity, and punishment of collusive behavior (Keeler, 1983). Unfortunately for the ICC, determining which rates were discriminatory proved to be outside the the scope of the ICA.

With regulation came the need for more accurate measures of shipment costs. Rail costing became a priority for the ICC. Established in 1939, Rail Form A (RFA) became the workhorse costing methodology for the ICC. RFA takes an accounting-based approach to explain the costs of performing various railroad activities, including track maintenance, freight car repairs, and road train inspection. Although RFA helped establish a consistent approach to allocating rail costs, the declining financial health of the rail industry post World War II along with several high profile railroad bankruptcies of the 1970s exposed the need for more rail rate flexibility. That is, if the industry were to survive and attract the capital necessary to sustain the rail network, then rates would need to be adjusted in order to protect profits.

IV.2.2 Partial Deregulation and Its Effect on the Industry

The financial ruin of several large railroads in the 1970s highlighted the need for more freedom in operational decisions. New competing forms of transportation such as barges, trucks, and airplanes reduced the market power of railroads. As demand for rail transportation fell, it became clear that the stability of the industry relied heavily on giving railroads more freedom and removing unneccessary regulations. Railroad deregulation began with the Railroad Revitalization and Regulatory Reform (4-R) Act of 1976, which reduced price regulations and gave firms more control over entry and exit decisions.

The Staggers Rail Act of 1980 relaxed constraints on the rates railroads can charge, the lines over which they can operate, on merger activity, as well as a wide array of other activities. Staggers substantially reduced the level of inefficiency in the market, increased productivity, and led to substantial declines in railroad costs and prices (Wilson and Burton, 1994; Bitzan, 2003). As a direct response to the high profile railroad failures of the 1970s, Staggers requires an annual revenue adequacy check to ensure the railroads, "achieve a rate of return sufficient to attract the capital necessary for long-term financial viability" (National Academies of Sciences, 2015). Some regulations remained in place, however, such as protecting rail shippers from excessive rates and from loss of service in markets that lacked alternative transportation options.

Current rail regulation relies on the Uniform Rail Costing System (URCS) to estimate the cost of a shipment.[1] Designed to "protect shippers from excessively high rates, to ensure revenue adequecy of the railroads, as well as the long-term financial viability of the industry" (STB, 2016b), URCS takes an accounting based approach to estimating the "variable cost" of a generic type of shipment. However, for contracting and regulatory purposes, rail rates are based on the origin-destination-commodity of the shipment. Defining a market at the origin-destination-commodity level results in an overwhelmingly large number of markets, as there exists over ten thousand rail stations and over one thousand different commodities at the STCC5 level. The "variable cost" generated by URCS is too generic for regulatory purposes, as railroad market concentration and operational expenses exhibit spatial heterogeneity, in part due to the massively multiproduct nature of the railroad industry. As a result, URCS has been heavily criticized. Regulators commissioned a report of the rail industry and found inconsistent revenue to variable cost ratios used for determining the reasonableness of a rate and recommended that "more appropriate measures of captivity should focus on the effects of the transportation market structure on rail rates, and by extension, markups" (Laurits R. Christensen Associates, 2009). Indeed, the Transportation Research Board found the URCS cost allocations to be invalid and unrealiable (National Academies of Sciences, 2015). Although URCS provides accounting costs at a disaggregate level, it is "unable to provide a cost measure that a profit-maximizing railroad would use to make operating decisions" and should be abandoned (Wilson and Wolak, 2016). Nevertheless, this congressionally mandated accounting based approach serves as the current regulatory tool for screening excessive rates.

[1]URCS documentation can be found at the following website
`https://www.stb.gov/stb/docs/URCS/URCS%20User%20Manual.pdf`

IV.2.3 Markups and Market Dominance

For regulatory purposes, rail shipments are classified into three rate categories. These include: 1. Exempt; 2. Contract; 3. Tariff rates. The first category contains shipments where the railroad faces adequate competition for the rail service from trucks. These shipments are automatically exempt from rate relief. The second category contains shipments that are negotiated contract rates, and these shipments are also automatically exempt from rate relief. The third category contains shipments that are transported under posted tariff rates and are confidential. If these goods cannot be competitively moved by truck, then they are eligible to be challenged and may be eligible for rate relief. To assess rate relief eligibility for category three shipments, regulations require that the revenue to URCS variable cost ratio exceed 180 percent.[2] Given that revenue to variable cost exceed 180 percent, the STB must also find that the railroad is market dominant over the movement, defined as "an absence of effective competition from other rail carriers or modes of transportation for the transportation to which a rate applies" (STB Ex Parte No 756, 2019). With the burden of proof for showing market dominance is on the shipper, rate relief is inaccessible to many market participants.

Given the rate is excessive and the railroad is found to be market dominant, shippers can use three different methodologies to contest the reasonableness of a rate. However, contesting the reasonableness of a rate is expensive and time-consuming (National Academies of Sciences, 2015). The Stand-Alone Cost (SAC) test establishes the cost of facilitating the movement to an individual consumer, as if a separate hypothetical railroad were built for just that traffic. This approach is inaccessible to small shippers and has been heavily criticized (Tye, 1986; Pittman, 2010; National Academies of Sciences, 2015).[3] In an attempt to make rate relief more accessible to

[2]Shipments with markups less than the threshold are automatically reasonable and cannot be challenged.

[3]Indeed, the author of the SAC test states it was "developed for an economic world of profit-

smaller shippers, the STB created the Simplified-SAC test (STB Ex Parte No 646, 2007). Unfortunately, the "simplified procedures have not overcome these deficiencies and in some respects have made matters worse" by offering even less predictible decision criteria (National Academies of Sciences, 2015). The STB also allows shippers to contest the reasonableness of a rate through the Three-Benchmark test "for which even a Simplified-SAC presentation would be too costly, given the value of the case" (STB Ex Parte No 646, 2007). Although this approach is relatively straight-forward to implement, it relies heavily on URCS to provide a realistic estimate of cost.

From 1996 to 2019, there have been only 51 rate cases filed with the STB, with only 12 resulting in an unreasonable rate.[4] In order to "reduce burdens on parties, expedite proceedings, and make the Board's rate relief procedures more accessible, especially for complainants with smaller cases", the STB recently approved an alternative way to gauge market dominance (STB Ex Parte No 756, 2020). This streamlined approach allows shippers to establish prima facie market dominance by satisfying the following factors:

1. The movement has an R/VC ratio of 180% or greater
2. The movement would exceed 500 highway miles between origin and destination
3. There is no intramodal competition from other railroads
4. There is no barge competition
5. There is no pipeline competition
6. The complainant has used truck for 10% or less of its volume (by tonnage) subject to the rate at issue over a five-year period and the complainant has no

constrained rate regulated monopoly, which is not at all like the largely unregulated, not profit-constrained and world of seven major rail networks that constitute this industry" (Faulhaber, 2014).

[4]Of the remaining 39 cases, two were withdrawn and 26 resulted in a settlement (STB, 2019a).

practical build-out alternative due to physical, regulatory, financial, or other issues (or combination of issues)

This approach highlights the interconnectedness of rail markups, intermodal, and intramodal competition. However, factors three, four, and five for intramodal and intermodal competition are qualitative.[5] The STB states that a shipper may satisfy these components by submitting a verified statement from an "appropriate official". Thus, access to the empirical relationship between shipment rail markups and transport competition may help regulators and market participants in assessing the reasonableness of a rate.

IV.3 Literature Review

This section highlights existing literature related to modeling operations of the firm and how these models have been applied to analyze the structure and competition of the railroad industry. The first subsection briefly describes the evolution of econometric models of costs and markups. The second subsection focuses on how these methodologies have been used to evaluate the structure of the railroad industry.

IV.3.1 Costs and Markups

There is a long history of empirical studies on cost and a long history of applications to the railroad industry.[6] There are many approaches to estimating costs, but most of the literature for the last 50 years has focused on the importance of using flexible forms to gauge the structure of costs and productivity through time. The workhorse of this literature is the transcendental logarithmic (translog) function (Christensen et al., 1973). Advantages of the translog function follow from its

[5]Intermodal and intramodal competition must transport the same commodity between the same origin-destination of the rate in question.

[6]See, for example, Keeler (1983); Chiang and Friedlaender (1985); Bitzan and Wilson (2003).

flexibility and relatively few restrictions it places on the production structure of the firm.

Quadratic cost functions provide a functional form that help account for non-linearities in the factors of production. Suggested by Baumol et al. (1983), Spady (1986) extends this approach by indexing individual production units. The quadratic cost function has a convenient aggregation property that helps facilitate its estimation econometrically. This flexible technique can be used to overcome issues of dimensionality by modeling aggregate costs with first and second moments of production units and remains parsimonious in parameters. Spady notes that these functions are capable of modeling multiproduct network technologies; however, this approach has yet to be applied to transport industries.

Markups and market power are of growing interests in applied economic research, with recent work suggesting market power supresses wages (Azar et al., 2018) and impacts macroeconomic growth (Loecker et al., 2019). Market power is important across various dimensions, with effects nationally and globally, both in traditional and nascent markets (Azar et al., 2017). Modern empirical industrial organization methods estimate markups by analyzing demand in the characteristics space as opposed to the product space (Berry et al., 1995). This approach has many attractive features that make the analysis for differentiated products tractible, starting with aggregate data and allowing for flexible substitution patterns between products. There also exists an alternative production-approach to recovering markups that relies on standard cost minimization conditions. Hall (1988) developed a model of firm behavior that recovers industry-specific markups from production data. Based on a production function, this approach relies on observing inputs and the total value of shipments. De Loecker and Warzynski (2012) adapt this approach by estimating markups through output elasticities.

IV.3.2 Identifying Non-Competitive Behavior

There is evidence that rail rates are responsive to the presence of transport competition (MacDonald, 1987). Rail rates for three major grains are estimated based on measures of intermodal and intramodal competition, such as proximity to competing railroads and distance to barge. The model suggests a move from monopoly to duopoly is associated with an 18% decrease in rates. Wilson and Train (2007) model transport mode choice for consumers faced with a choice between rail and barge. Their results suggest access costs, barge and rail rates, and shippers' attributes play an important role in determining which mode consumers select. Anderson and Wilson (2005) examine the relationship between truck-barge and railroads. Their theoretical model suggests a direct relationship between markups and mode choice. In the National Academies of Sciences (2015) study, the authors introduce a benchmarking approach. In this approach, they estimate a pricing relation with measures of competition and identify potentially non-competitive rail rates in excess of rates expected in competitive markets. Controlling for proximity to transport competition allows them to construct benchmark competitive prices, which they compare to actual prices to assess the reasonableness of a rate. In a more recent study, Wilson and Wolak (2020) refine the benchmarking approach to handle additional commodities. This empirical relationship is important in designing tranport regulations; however, a more relevant measure of rate reasonableness should also incorporate costs.

There is a long history of estimating cost functions for railroads; however, many issues that were raised are still of concern today (Winston, 1985). In contrast to the disaggregate accounting approach of URCS, the academic literature of railroad economic costs and markups are aggregate in nature and estimate the average cost over the network (Keeler, 1983; Chiang and Friedlaender, 1985; Bitzan and Wilson, 2003) or the average markup over the network (Ivaldi and McCullough, 2007; Coublucq, 2013; McKenzie and Wilson, 2016). Most rail cost studies use aggregate measures of output and assume railroad output is homogeneous (Spady and Friedlaender, 1978; Caves et al., 1981; Harmatuck, 1981; Caves et al., 2002). Brown et al. (1979) relax this assumption and show the neoclassical cost function provides a flexible multiproduct approach to estimating rail costs. Chiang and Friedlaender (1985) extend the single generic output translog cost function to multiple generic outputs in the motor carrier industry and Bitzan and Wilson (2003) incorporate product heterogeneity via a hedonic translog cost function to model rates in the railroad industry.[7] However, they find that the translog cost function does not perform well for costing individual shipments. Ivaldi and McCullough (2007) use a Generalized McFadden cost function and estimate car-type-specific costs to assess whether Class I railroads are revenue adequate. This approach incorporates the multiproduct nature of railroads but is unable to provide costs at a disaggregate level.

Markups and market dominance in the railroad industry are of considerable interest. Founded in antitrust litigation, the concept of market dominance incorporates both product and geographic competition (Eaton and Center, 1985). Wilson (1996) derives a theoretical model of railroad pricing and markups to examine the regulatory rules defining market dominance. Coublucq (2013) estimates a structural model of the railroad industry to examine the impact of mergers and acquisitions post-Staggers on costs, markups, and consumer welfare. The results suggest increases in firm markups throughout time at an aggregate level. McKenzie and Wilson (2016) estimate markups and scale elasticities in the railroad industry based on production relations. They estimate the model in a Bayesian framework and find markups are well in excess of marginal costs. Their model provides estimates of rail specific markups, which represent the average markup generated from traffic on each firm's network; however, averages often mask underlying heterogeneity.

[7] See Bitzan and Wilson (2007) Table B.1 for a more detailed timeline of advances in rail costing techniques.

IV.4 Conceptual Framework

The problem of estimating markups is isomorphic to the problem of estimating costs. To obtain shipment costs, I model firm-level railroad operations using a quadratic cost function proposed by Spady (1986). The main benefit of modeling railroad costs with this method is that cost estimates reflect shipment features that may influence cost, and thus, markups. The firm can view its costs of producing vector output y at factor prices p under technological conditions t; denoting (y, t) by z:

$$c = \alpha_0 h_0 + \sum_k \alpha_k h_k(p) z_k + \sum_k \sum_m \beta_{km} \phi_{km}(p) z_k z_m \tag{IV.1}$$

An attractive feature of the quadratic cost function resides in its aggregation properties. Suppose that IV.1 has s shipments and there exists a price index $h(p)$ that is common to all factors of production.[8] Denote the z and c of the i^{th} shipment by z^i and c^i, and the mean of z by $\bar{z}$. Defining $\epsilon^i = z^i - \bar{z}$ allows IV.1 to be written as:

$$c^i = \alpha_0 h(p) + \sum_k \alpha_k h(p)(\bar{z}_k + \epsilon^i_k) + \sum_k \sum_m \beta_{km} h(p)(\bar{z}_k + \epsilon^i_k)(\bar{z}_m + \epsilon^i_m) \tag{IV.2}$$

Summing IV.2 over the s shipments yields:

[8] The common price index assumption can be relaxed; however, access to a common price index keeps the model econometrically tractible.

$$C = \sum_s c^i \tag{IV.3}$$

$$= h(p)s\left[\alpha_0 + \sum_k \alpha_k \bar{z}_k + \sum_k \sum_m \beta_{km}(\bar{z}_k \bar{z}_m + \sigma_{km})\right] \tag{IV.4}$$

where $\sigma_{km} = \frac{1}{s}\sum_s \epsilon_k^i \epsilon_m^i$ represents the covariance of z_k and z_m. A convenient reexpression of IV.3 is:

$$\bar{c} \equiv \frac{C}{h(p)s} \tag{IV.5}$$

$$= \alpha_0 + \sum_k \alpha_k \bar{z}_k + \sum_k \sum_m \beta_{km}(\bar{z}_k \bar{z}_m + \sigma_{km}) \tag{IV.6}$$

where $\bar{c}$ is the average cost per shipment and $c(\bar{z})$ is the production unit level quadratic cost function at mean z. Thus, the number of units and the means and variances of the outputs and characteristics provide an exact representation of the aggregate technology (Spady, 1986).

Modeling shipment costs allows the construction of shipment price-cost markups given by:

$$\mu_i = \frac{r_i}{c_i} \tag{IV.7}$$

where μ_i is the shipment price-cost markup, r_i is the shipment rail rate, and c_i is shipment cost for shipment i. With markups at a disaggregate level, I model the spatial relationship between shipment markups and proximity to transport competition:

$$\log(\mu_i) = \phi_0 + water_i + rail_i \tag{IV.8}$$

where $water_i$ represents competition of waterway transport and $rail_i$ represents competition of rail transport. This approach incorporates the spatial heterogeneity of rail markups as they relate to transport competition, an important component of market dominance inquiry.

IV.5 Data

The primary sources of the data are the Surface Transportation Board (STB) confidential Annual Carload Waybill Sample, the R-1 Annual Report of Finances and Operations, the Oakridge National Laboratory CTA Railroad Network, and the U.S. Army Corps of Engineers Port Series. The waybill data is a confidential and detailed dataset that contains shipment and product characteristics. In the R-1 data, I observe railroad cost components that I use to construct a measure of total annual cost for each railroad. The Oakridge data provides every railroad in North America that has been active since 1993, which I use to construct measures of intramodal competition. The Port Series data provides every port in the U.S., which I use to construct measures of intermodal competition.

The waybill data provides shipment product characteristics for over 369 million shipments covering all Class 1 railroads over the 2000 through 2016 period.[9] These data are a stratified random sample which represents at least 2.5% of all shipments each year. To account for the stratified sampling procedure, I weight each observation by the inverse of its sampling probability.[10] Observations include information of each shipment's rate, URCS variable cost, distance, tons, cars, car type, origin, and destination. The waybill data also contain the Standard Point Location Code (SPLC) that identifies the origin and destination of each shipment. Throughout the sample, there are 119 firm years. The seven Class 1 railroads are comprised of BNSF Railway Co., CSX Transportation, Grand Trunk Corporation[11], Kansas City South-

[9] Due to substantial merger activity in the 1980's and 90's, I focus on data beginning in year 2000.
[10] Wolfe (2004) provides a more complete description of the waybill data.
[11] Canadian National's operations

ern Railway, Norfolk Southern, Soo Line Corporation[12], and Union Pacific Railroad. In 2016, these seven railroads accounted for 68% of US freight rail mileage, 88% of employees, and 94% of revenue (JOC, 2016).

As noted in Ivaldi and McCullough (2007), different car types have different cost and demand characteristics. Inspection of the data suggests that there is a near perfect correspondence of commodity to car type. Thus, I follow the literature and group each shipment into one of five car type categories: box cars, gondola cars, hopper cars, flat cars, and tank cars. Figure III.1 visualizes the relationship between commodity and car type with firm-year averages over the sample. The top displays the number of tons of each commodity by car type. The bottom displays revenue of each commodity by car type. Commodity and car type are highly correlated, as the major commodities tend to travel in predictable car types. I leverage this relationship in the empirical section to incorporate the multiproduct features of railroad operations while also keeping the cost function tractible econometrically.

I use the R-1 data for firm-year components of cost, which provide financial and operating information for Class 1 railroads. The R-1 report is the result of railroads reporting to the Interstate Commerce Commission (ICC) and the Surface Transportation Board (STB) and is available for all railroads and all years of the sample. Based on these self-reported figures, I follow the literature (Bitzan and Wilson, 2007) and construct an annual measure of total cost for each of the seven Class 1 railroads:

$$C = OpCost - CapExp + RoiRd + RoiLcm + RoiCrs \tag{IV.9}$$

where C is total annual cost, $OpCost$ is operating cost, $CapExp$ is capital expenditure, $RoiRd$ is return on investment in road, $RoiLcm$ is return on investment in locomotives, and $RoiCrs$ is the return on investment in cars.[13] Figure IV.1 displays

[12]Canadian Pacific's operations.
[13]These variables, and all other variables, are defined in Table IV.1.

annual firm-level cost for the Class 1 railroads.

Table IV.1
Variable Definitions

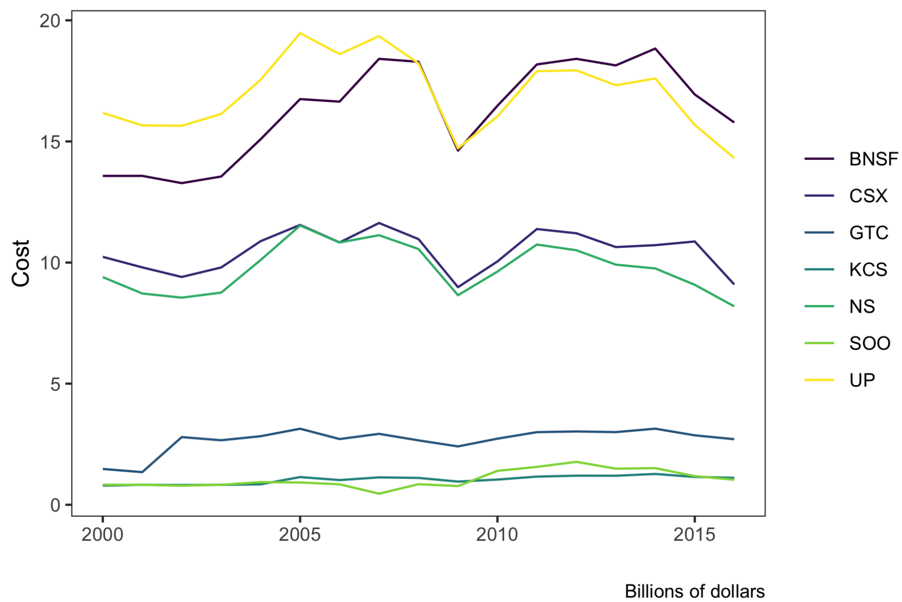
Variable	Definition	Source
C	Total cost	R1
s	Number of shipments	Waybill sample
$\bar{c}$	Real total cost per shipment	R1, Waybill
d	Distance (miles)	Waybill sample
t	Tonnage	Waybill sample
u	Unit train	Waybill sample
$CarType$	Type of rail car	Waybill sample
$h(p)$	Railroad cost adjustment factor	AAR Railroad Facts
$OpCost$	Railroad operating cost	R1, Sched. 410, ln. 620, Col F
$CapExp$	Capital expenditures	R1, Sched. 410, ln. 12-30, 101-109, col. F
$RoiRd$	Return on investment in road	$(RoadInv - AccDepr) * CostK$
$RoadInv$	Road investment + $CapExp$ (cumulative)	R1, Sched. 352B, ln. 31, col. B
$AccDepr$	Accumulated depreciation in Road	R1, Sched. 335, ln. 30, col. G
$CostK$	Cost of capital	AAR *Railroad Facts*
$RoiLcm$	Return on investment in locomotives	$[(IboLoco + LocInvl)-$ $(AcdoLoco + LocAcdl)] * CostK$
$IboLoco$	Investment base in owned loc.	R1, Sched. 415, ln. 5, col. G
$LocInvl$	Investment base in leased loc.	R1, Sched. 415, ln. 5, col. H
$AcdoLoco$	Accum. depr. owned loc.	R1, Sched. 415, ln. 5, col. I
$LocAcdl$	Accum. depr. leased loc.	R1, Sched. 415, ln. 5, col. J
$RoiCrs$	Return on investment in cars	$[(IboCars + CarInvl)-$ $(AcdoCars + CarAcdl)] * CostK$
$IboCars$	Investment base in owned cars	R1, Sched. 415, ln. 24, col. G
$CarInvl$	Investment base in leased cars	R1, Sched. 415, ln. 24, col. H
$AcdoCars$	Accum. depr. owned cars	R1, Sched. 415, ln. 24, col. I
$CarAcdl$	Accum. depr. leased loc.	R1, Sched. 415, ln. 24, col. J
$SPLC$	Standard Point Location Code	Waybill sample
$RR - Mi$	Railroad within X miles	CTA Railroad Network
$Port - Mi$	Port within X miles	Port Series data

Notes: All R-1 variables available at the annual level. All Waybill variables are aggregated to the annual level, from data available at the shipment level.

I use the Oakridge and Port Series data to construct measures of transport competition. The Oakridge data provide spatial coordinates for every railroad route that has been active throughout the sample.[14] I use these data to quantify railroad competition, where I measure the distance from each shipment SPLC to competing railroads. Similarly, I use the Port Series data to measure the presence of water competition. These data provide the location of ports on U.S. waterways along with the

[14]`http://www-cta.ornl.gov/transnet/RailRoads.html`

Figure IV.1
Annual Cost for Class I Railroads

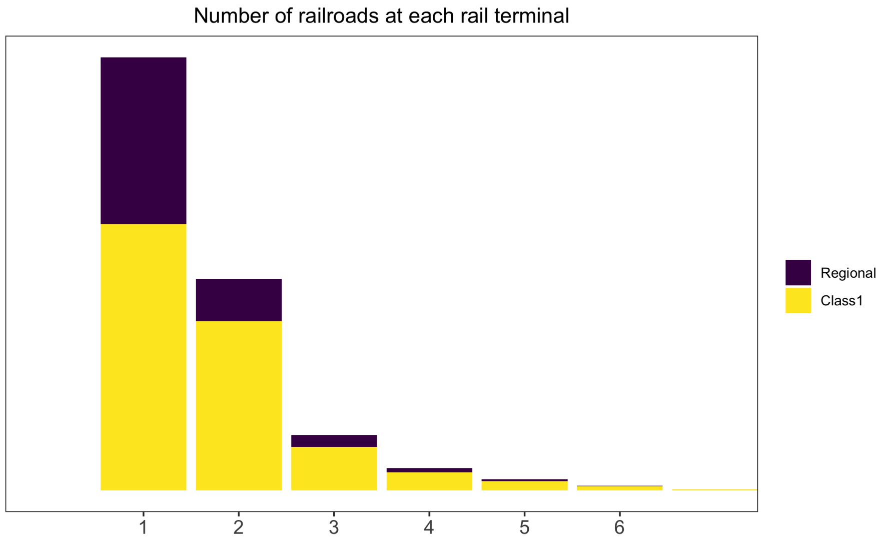


commodities handled by each port.[15] I use these data to quantify waterway competition by measuring the distance from each shipment SPLC to the nearest port. For rail competition, I observe 37,721 SPLC points. Figure IV.2 displays a histogram of rail competition for all SPLCs in the US. Notice that the modal SPLC is serviced by one Class 1 railroad and one regional railroad.

Finally, I follow the literature and account for changes in factor prices using the productivity-adjusted Railroad Cost Adjustment Factor (RCAF-A) index (Ivaldi and McCullough, 2007). This index is used for regulatory purposes and provides a convenient measure that reflects changes in the price of major railroad operating costs such as labor, fuel, materials, equipments rents, and interest on debt (National Academies of Sciences, 2015). The RCAF-A is published annually by the Association of American Railroads (AAR) and submitted to the STB for approval.[16]

[15] `http://www.navigationdatacenter.us/ports/ports.htm`
[16] `https://www.aar.org/wp-content/uploads/2018/03/Index_RCAFDescription.pdf`

Figure IV.2
Railroad Market Concentration



IV.6 Results

In this section, I present the results for shipment price-cost markups and how they relate to transport competition. The first subsection estimates a quadratic cost function for railroads. The second subsection constructs markups by pairing cost estimates with observed rates. The final subsection estimates these markups as a function of transport competition.

IV.6.1 Cost

In this section, I present the results for shipment costs. I start by using the full waybill sample to estimate a quadratic cost function for railroads. The variables described in the preceding paragraphs will now be used to estimate equation IV.5. In this regard, I estimate shipment costs using the following form:

$$\bar{c}_{it} = \sum_k \alpha_k \bar{z}_k + \sum_k \sum_m \beta_{km}[\bar{z}_k \bar{z}_m + \sigma_{km}] + \kappa_{it} + \phi_i + \lambda_t + \varepsilon_{it} \tag{IV.10}$$

where $\bar{c}_{it}$ is firm cost per shipment for firm i. Product and technological characteristics ($\bar{z}_k$) include average distance, average tons, and average unit. Average unit is defined as the percent of total shipments that have 50 or more cars. Car type is defined as the percent of total shipments using the specific car type. Additionally, σ_{km} represents the covariance between product characteristics, such as average distance, average tons, and average unit. Car type controls κ_{it} represent the percentage of shipments that use a specific car type within a given firm-year. Distance, tons, and unit help control for product characteristics, while car type controls proxy for commodity. Firm fixed effects (ϕ_i) control for firm level differences that affect firm cost per shipment. Year fixed effects (λ_t) control for changes that affect cost in all markets.

Table III.3 displays the results of equation IV.10, where average distance, average tons, and average unit are statistically significant across all specifications. Note that cost is increasing in ton-miles ($\bar{d} \cdot \bar{n}$) and is statistically significant across all specifications. I use model (4) as the preferred specification for the remainder of the analysis, as it accounts for features that are known to be associated with costs and also incorporates the multiproduct nature of railroad operations through car type controls. Recall that the quadratic cost function allows for non-linearities in the production units. Thus, to better understand the marginal impact for product and technological characteristics, I present marginal cost per shipment in Figure III.2. In line with economic theory, costs are increasing in both distance and tons.

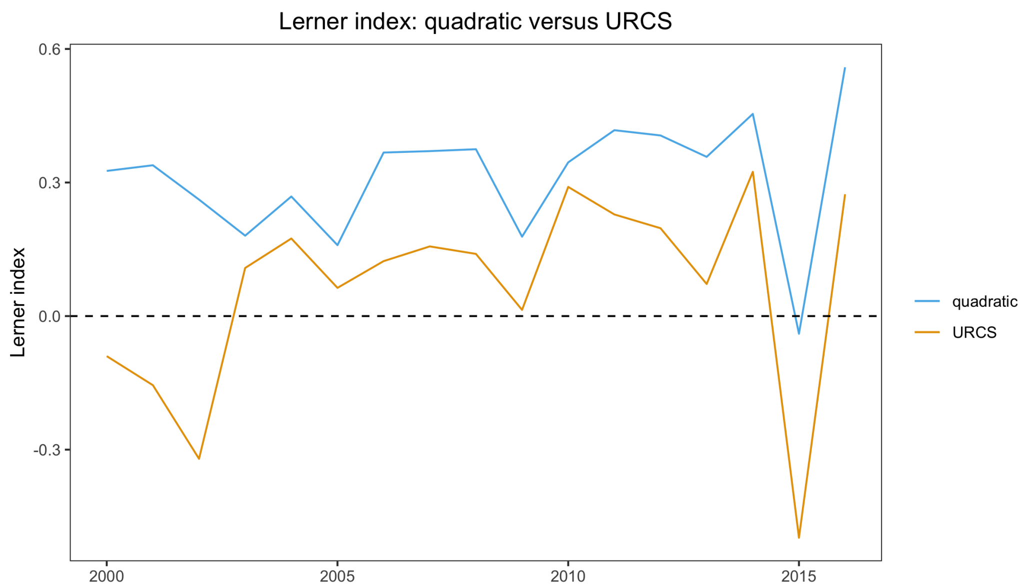
IV.6.2 Markups

In this section, I use the results from the quadratic cost function along with observed rail rates to construct shipment price-cost markups. I construct Lerner indices given by:

$$\eta = \frac{\sum_{i=1}^{S} \frac{r_i - c_i}{c_i}}{S} \tag{IV.11}$$

where η is the Lerner index, r_i is the rate for shipment i, c_i is the cost for shipment i, and S is the total number of shipments. In Figure IV.3, I present a time-series of markups calculated using different cost methodologies. It appears that, on average, both costing approaches are picking up similar market trends throughout time. Note that although URCS suggests competitive behavior, estimating shipment costs with the quadratic cost function suggests relatively healthy markups. Note that while URCS suggests 20 to 30% of shipments have costs exceeding revenue, the quadratic approach reduces amount to 7%.

Figure IV.3
Lerner Index Comparison



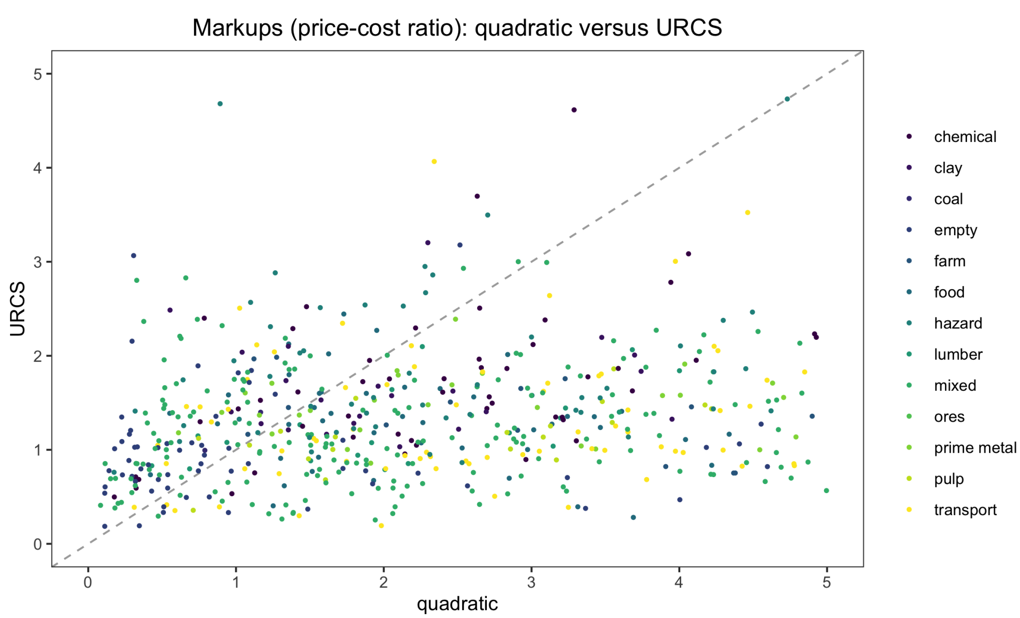
Recall that for regulatory purposes, only shipments that exceed a price-cost markup threshold are eligible for rate relief inquiry. To better understand shipment markups, I compare quadratic price-cost markups to URCS price-cost markups for identical shipments, given by:

$$\mu_i = \frac{r_i}{c_i} \tag{IV.12}$$

where μ_i is the price-cost markup, r_i is the rate, and c_i is the cost for shipment

i. If the quadratic approach and the URCS method yielded identical estimates for markups, then plotting the estimated values against each other graphically would yield a 45-degree line. Figure IV.4 compares the price-cost markups for a random sample of 1,000 shipments. The two cost approaches provide similar markups for smaller shipments; however, as the value of the shipment increases, the quadratic model estimates markups larger than those produced using URCS. Notice the URCS approach yields a clustering of shipments close the price-cost markup threshold of 180%, which suggests railroads price shipments near the threshold to increase profits and avoid the dispute resolution process.[17]

Figure IV.4
Markups Comparison

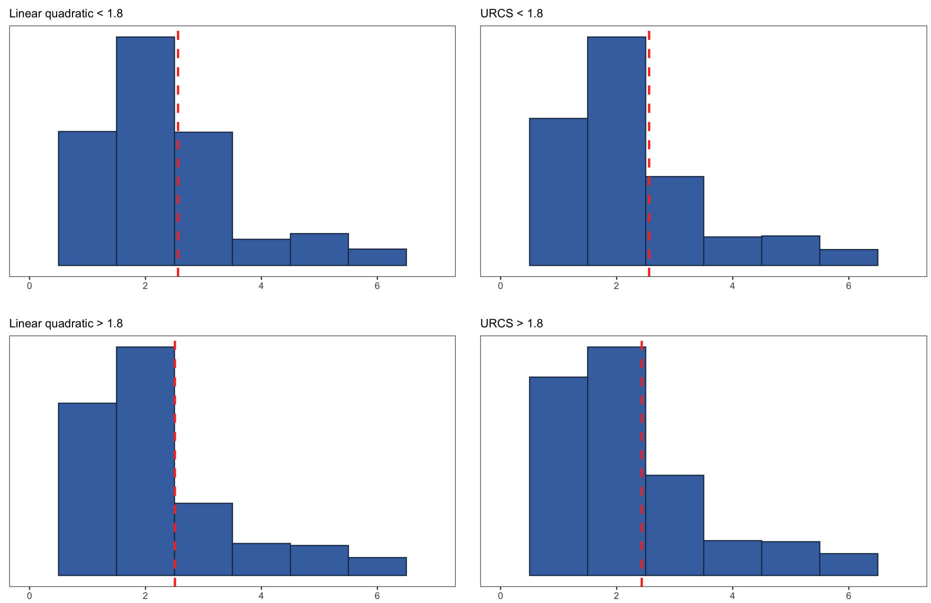


To better understand how these shipment markups relate to intermodal competition, I group shipments based on the price-cost markup threshold rule of 180. Figure IV.5 displays the number of Class 1 railroads within 10 miles of the origin and Figure IV.6 displays the number of Class 1 railroads within 10 miles of the destination.

[17]It is important to note that the disaggregate price-cost markups generated by the quadartic approach are similar to a previous study that estimate aggregate price-cost markups (Ivaldi and McCullough, 2007).

Recall that exceeding the rule of 180 for shipment URCS markups is a necessary condition for a shipment to be eligible for rate relief. It appears that the degree of competition does not vary much based on whether the shipment is above or below the price-cost markup threshold.

Figure IV.5
Markup Threshold and Intramodal Competition at Origin

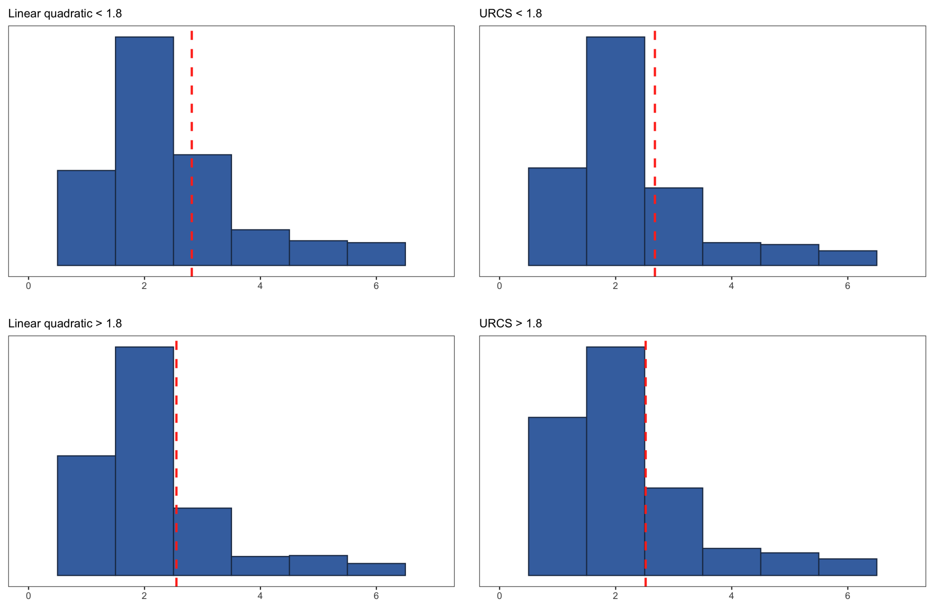


IV.6.3 Markups, Intramodal, and Intermodal Competition

Market dominance inquiry relates shipment price-cost markups to transport competition. In this section, I present results that measure the relationship between shipment markups, intramodal, and intermodal competition. I start by mapping the spatial relationship between shipment quadratic markups and intramodal competition using bidirectional maps. Figures IV.7 display the relationship between origin-county and destination-county level shipment markups as they relate to the degree of intramodal competition.[18] I define intramodal competition as the number of Class 1

[18]Figure IV.7 displays the average shipment markup across all commodities, but the results are disaggregate and could be analyzed by commodity.

Figure IV.6
Markup Threshold and Intramodal Competition at Destination

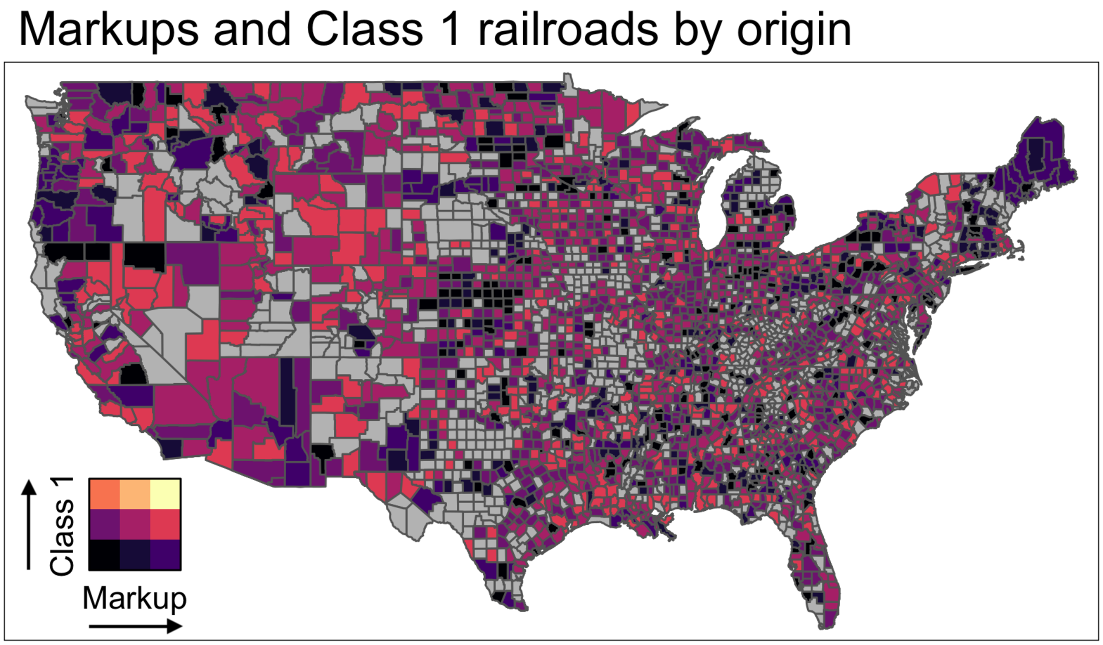


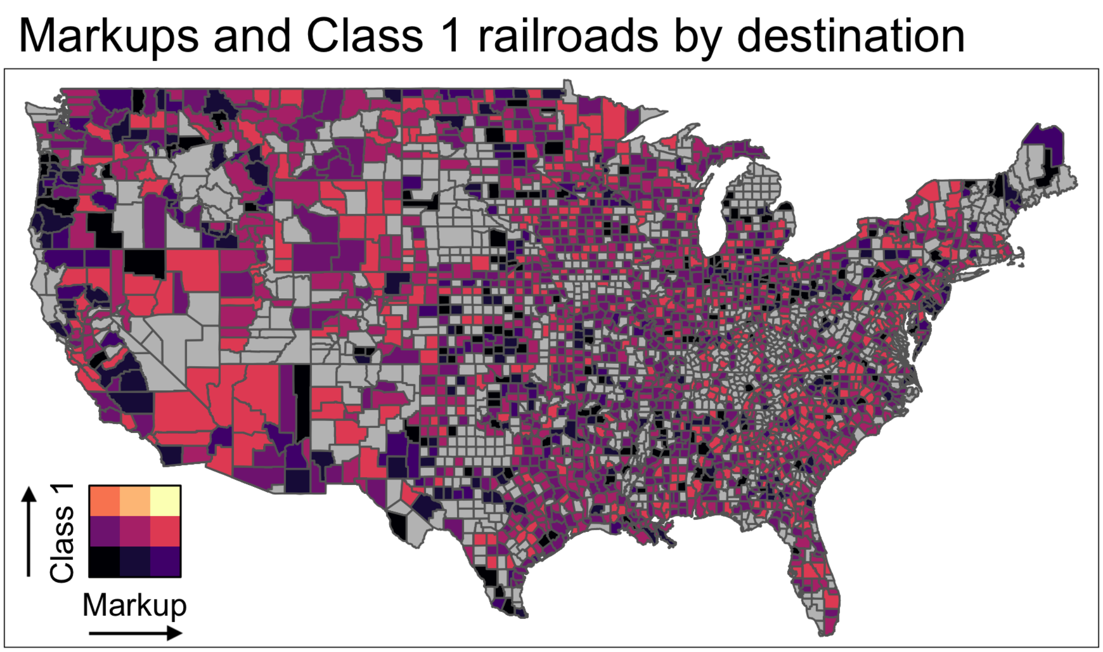
railroads within a given county.

To start, note that the gray areas represent counties in which there do not exist any SPLCs. The top map represents markups and the number of Class 1 railroads within a given county, while the bottom map represents markups and the number of all railroads within a given county. The lower left part of the legend represents counties that have low markups and low degrees of intramodal competition. The upper right part of the legend represents counties that have high markups and high degrees of intramodal competition. Although this region of the legend indicates high markups, the high degree of intramodal competition usually indicates a lack of market dominance over the movement. The bottom right corner of the legend represents counties that have high markups and low degrees of intramodal competition. This purple area is of interest in market dominance inquiry, as it may indicate that captive shippers are facing excessive rates with few alternatives.

For Class 1 rail competition by origin, notice that the purple area of interest is predominatly in northern California, the Pacific Northwest, the Northeast, and

Figure IV.7
Markups and Class I Competition



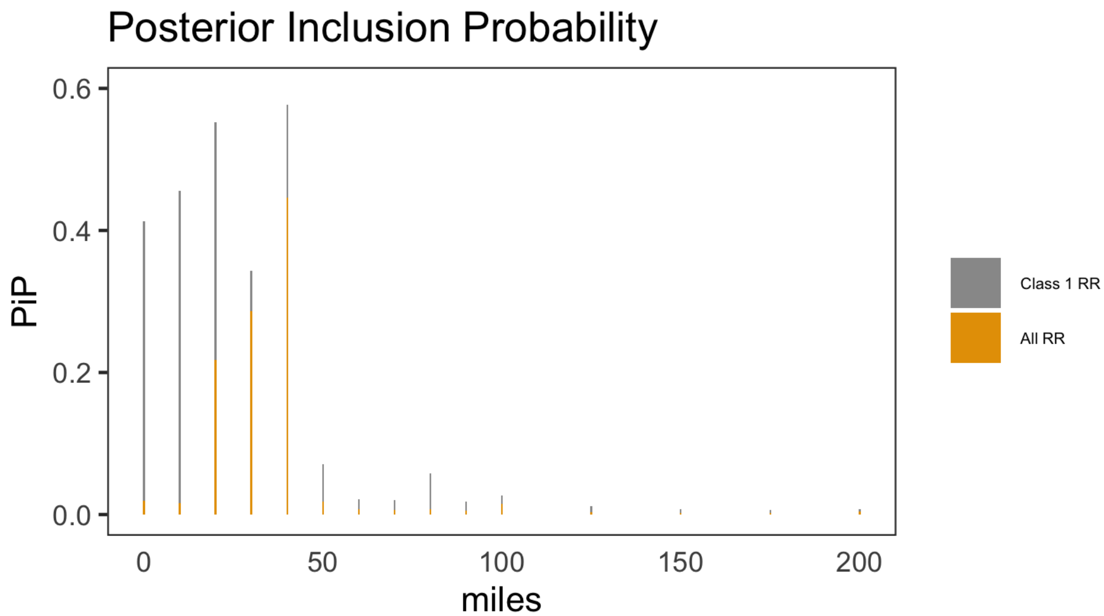


some areas in Texas and South Dakota. This suggests that shipments that originate on the coasts may face high markups and few alternative options via Class 1 rail. Additionally, the areas in Texas and South Dakota indicate that shipments originating in these landlocked areas may also face high markups with few alternatives. For Class 1 rail competition by destination, notice that the purple area of interest is predominatly in northern California, Oregon, Maine, Arizona, and New Mexico. This suggests that shipments that terminate on the coasts may face high markups and few alternative options via Class 1 rail. Additionally, the areas in Arizona and New Mexico indicate that shipments terminating in these landlocked areas may also face high markups with few alternatives.

I quantify the model uncertainty of estimating shipment rail markups based on proximity to transport competition. Incorporating measures of spatial competition may help explain variation in markups; however, there exists model uncertainty regarding which distances should be included in the model. I quantify this uncertainty with Bayesian model averaging (BMA), which I implement with the Markov-chain Monte Carlo Model Composition (MC^3) approach of Madigan and York (1993). I set benchmark priors (Fernández et al., 2001) that assign equal weight to all distances of competition. Figure IV.8 displays the posterior inclusion probability for competing railroads, which estimates shipment markups based on distance to Class 1 railroads and distance to all railroads. The results suggest that rail markups are associated with competition from Class 1 railroads within a distance of 10 miles and competition from all railroads within a distance of 40 miles.

Next, I quantify the relationship between shipment markups, intramodal, and intermodal competition. Economic theory in competitive markets suggests an inverse relationship between markups and the degree of competition. To test this empirically, I estimate shipment price-cost markups using the following form:

Figure IV.8
Markups and Proximity to Transport Competition



Number of competing modes of transport within a given distance

$$\log(\mu_{itm}) = \beta_0 + \beta_{ft} + \beta_{ol} + \sum_{k=1}^{10} \beta_k X'_{k,itm} + \varepsilon_{itm} \quad \text{(IV.13)}$$

where μ_{itm} is the shipment price-cost markup for shipment i in time t for commodity m. The model assumes shipment price-cost markups are a function of distance (X_1), tons (X_2), the number of Class I railroads within 10 miles of the origin (X_3) and destination (X_4), the number of all railroads within 40 miles of the origin (X_5) and destination (X_6), the distances of the origin (X_7) and destination (X_8) from the nearest port that handles a specific commodity, an interaction between the number of Class I railroads within 10 miles of the origin and the distance from the nearest port (X_9), and an interaction between the number of Class I railroads within 10 miles of the destination and the distance to the nearest port (X_{10}). These shipment characteristics were selected based on previous empirical research on the determinants of shipment rates.[19] Tons and distance are measured in natural logarithms. Finally, fixed effects

[19]See, for example, MacDonald (1987); Wilson and Burton (1994); Wilson and Wolak (2020).

are included: β_{tf} for firm-month-of-year and β_{ol} for the state origin-destination of the shipment.

I follow the literature by focusing on the primary commodities of grain, coal, petroleum, and chemical and display the results in Table IV.2. Across the primary commodities and evaluated at mean values of other variables, I find that a movement from monopoly to duopoly is associated with an average 6.8% decline in rail markups. The results suggest that shipment markups are statistically significantly associated with both intramodal and intermodal competition. Distance to ports is positive across almost all primary commodities, suggesting that landlocked shippers may face relatively higher markups. The interaction between intramodal and intermodal competition across all primary commodities suggests that nearby ports decrease the impact of rail competition on rail markups, as shippers are able to substitute away from rail and towards movement by barge.

Finally, I evaluate the marginal effects of intramodal and intermodal competition on shipment markups for the primary commodities of grain, coal, petroleum, and chemical products. Figure IV.9 presents the marginal effects for these primary commodities based on the number of Class 1 railroads within 10 miles of the origin and the distance from the origin to the nearest port. For coal, petroleum, and chemical shipments, my model suggests the number of Class 1 competitors at the origin constrains rail markups. For coal and chemical shipments, ports close to the origin decrease the impact of rail competition on rail markups. Abiding by the rule of 180, my model suggests that most grain shipments as well as coal shipments with an origin over 200 miles from a port may be eligible for rate relief. Figure IV.10 modifies this analysis and presents the marginal effects based on the number of Class 1 railroads within 10 miles of the destination and the distance from the destination to the nearest port. For petroleum and chemical shipments, my model suggests the number of Class 1 competitors at the destination constrains rail markups. The rule of 180 suggests

Table IV.2
Rail Markups and Transport Competition

	log(markup)			
	Grain	Coal	Petroleum	Chemical
C1 RR in 10m of origin	0.012***	0.070***	−0.024***	−0.031***
	(0.003)	(0.011)	(0.005)	(0.003)
C1 RR in 10m of destination	0.012***	0.052***	−0.024***	−0.046***
	(0.003)	(0.019)	(0.004)	(0.003)
RR in 40m of origin	−0.015***	0.005	0.005***	0.002*
	(0.001)	(0.003)	(0.002)	(0.001)
RR in 40m of destination	0.002	−0.006**	−0.001	−0.003***
	(0.001)	(0.003)	(0.001)	(0.001)
Origin miles to port	0.0003***	0.004***	0.001***	0.001***
	(0.00003)	(0.0003)	(0.0001)	(0.00004)
Destination miles to port	0.0002***	0.002***	0.0001**	0.0001***
	(0.0001)	(0.0004)	(0.0001)	(0.00004)
Origin miles to port	−0.00003**	−0.001***	−0.0003***	−0.0003***
· C1 RR in 10 miles	(0.00001)	(0.0002)	(0.00003)	(0.00002)
Destination miles to port	−0.0001***	−0.0002	−0.0001***	0.0001***
· C1 RR in 10 miles	(0.00002)	(0.0002)	(0.00003)	(0.00002)
FEs	Yes	Yes	Yes	Yes
Observations	36,440	9,816	18,706	90,363
R^2	0.846	0.898	0.811	0.706

Notes: This table reports estimates of Equation IV.8. An observation is a shipment. The dependent variable is the log of the markup. Fixed effects include firm-month-of-year and state origin-destination. Bootstrap standard errors in parentheses. Stars indicate p values: *p<0.1; **p<0.05; ***p<0.01.

regulators may be interested in taking a closer look at grain markups for shipment destination that have few Class 1 competitors and are far from ports.

IV.7 Concluding Remarks

Most firms are multiproduct, but traditional analysis of costs focus on single products. This is especially true in the massively multiproduct railroad industry, where regulators are congressionally mandated to use an accounting procedure to measure the cost and markup of a generic shipment. Eligibility for rate relief in market dominance inquiry depends on how these markups relate to transport competition, which is based on subjective testimony from an expert witness. Thus, regulators may benefit from an empirical analysis of how shipment costs and markups relate to transport competition.

To assist regulators and market participants in market dominance inquiry, I developed and estimated a model of railroad costs and markups in a way that retained their disaggregate properties. In contrast to the heavily criticized regulatory approach of allocating accounting costs of a generic shipment, my model provides shipment costs and markups that are grounded in economic theory. I use these results to provide empirical evidence of how transport competition impact shipment markups and find evidence of commodity heterogeneity. I find that a movement from monopoly to duopoly is associated with an average 6.8% decline in rail markups. The results suggest that nearby ports decrease the impact of rail competition on rail markups. These results can be operationalized by regulators and market participants to assess the reasonableness of a rate and to streamline and expedite market dominance inquiry.

The analysis provides an alternative approach to evaluating costs and markups and then illustrates how key relevant variables of competition may improve and ad-

Figure IV.9
Markups and Class I Competition within 10 Miles of the Origin

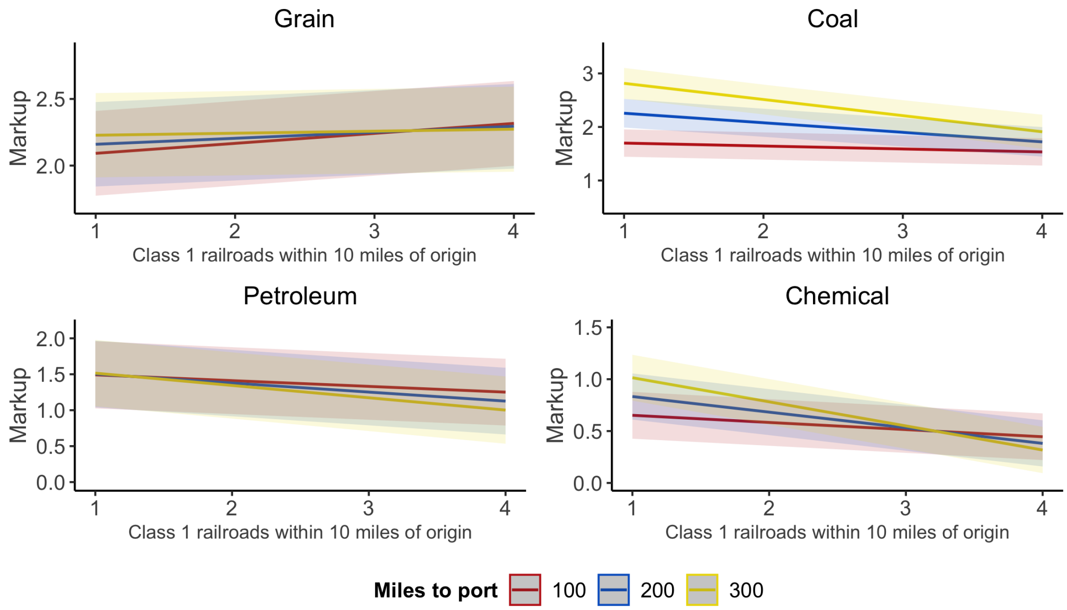
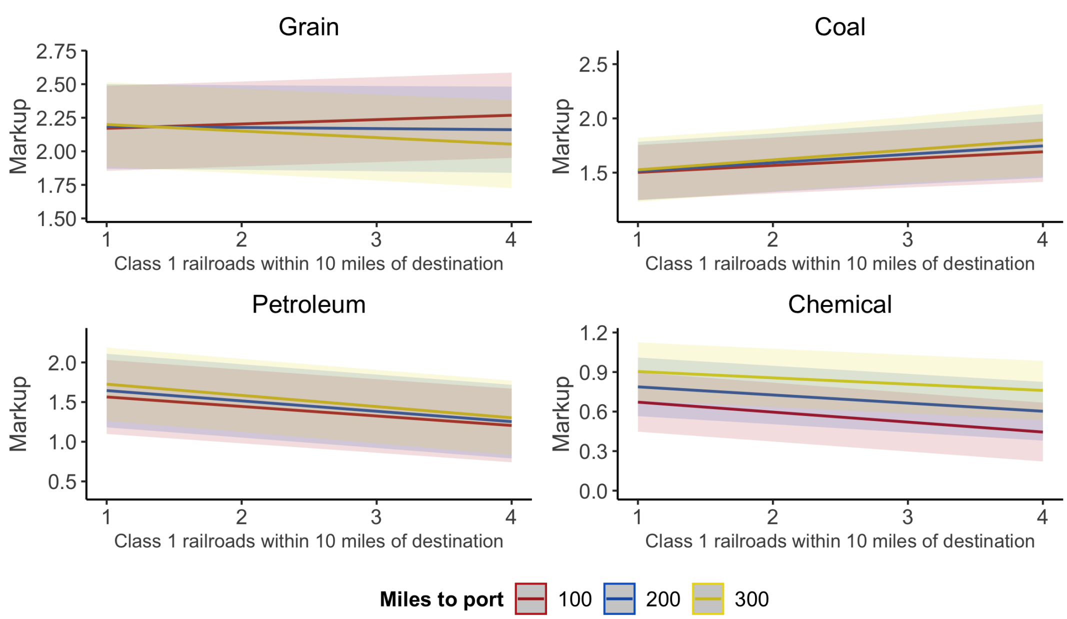


Figure IV.10
Markups and Class I Competition within 10 Miles of the Destination



vance our understanding of market dominance in the railroad industry. Collecting firm-level costs at a more regular interval, such as quarterly, would allow regulators to overcome dimensionality issues associated with estimating shipment costs. The recently approved streamlined approach to market dominance inquiry also requires an assessment of competition from pipeline. Although this form of intermodal competition is only relevant for a few commodities, future research may benefit from incorporating this alternative mode of transport into the model.

CHAPTER V

DISSERTATION CONCLUSION

In this dissertation, I investigate the industrial organization of transport markets in the United States. In the second chapter of my dissertation, I demonstrate that Bayesian techniques can improve forecasts of waterborne commerce along the inland waterway network. This approach to comparing and incorporating alternative models is especially well-suited for situations in which there exists substantial model uncertainty, as is present within the Lock Performance Monitoring System. As transport markets have temporal components, I account for this by implementing the model with rolling-window techinques.

Transporting shipments by rail provides an alternative mode of transport. However, rail regulation requires accurate measures of railroad costs, and the current regulatory accounting based approach is heavily critized. In the third chapter of my dissertation, I develop and estimate a multiproduct cost function for railroads that can provide measures of rail shipment cost. I compare my cost estimates to those generated by the current regulatory approach and find that the current approach overstates costs, implying that more shippers may be eligible for regulatory relief and potential reparations.

Regulators of the railroad industry use rail costing to assist in regulatory review by quantifying the price-cost markup in conjunction with a qualitative assessment of transport competition along the route. In the fourth chapter of my dissertation, I operationalize the results from the multiproduct cost function to construct economic price-cost markups for rail shipments at an extremely disaggregate level. I then explain these rail markups econometrically in terms of transport competition in order to provide regulators and market participants a quantitative measure of how rail markups vary based on proximity to transport competition. This approach can be operationalized by regulators and market participants to assess the reasonableness of a rate and to streamline and expedite regulatory procedures.

APPENDIX

Figure A.II.1
Posterior Inclusion Probability: Total Commodities

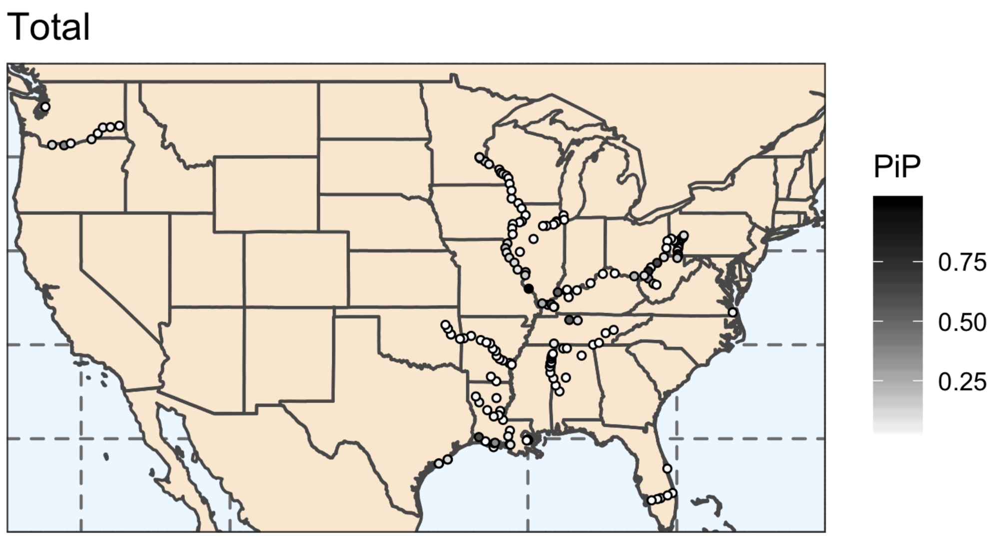


Figure A.II.2
Posterior Inclusion Probability: Primary Commodities

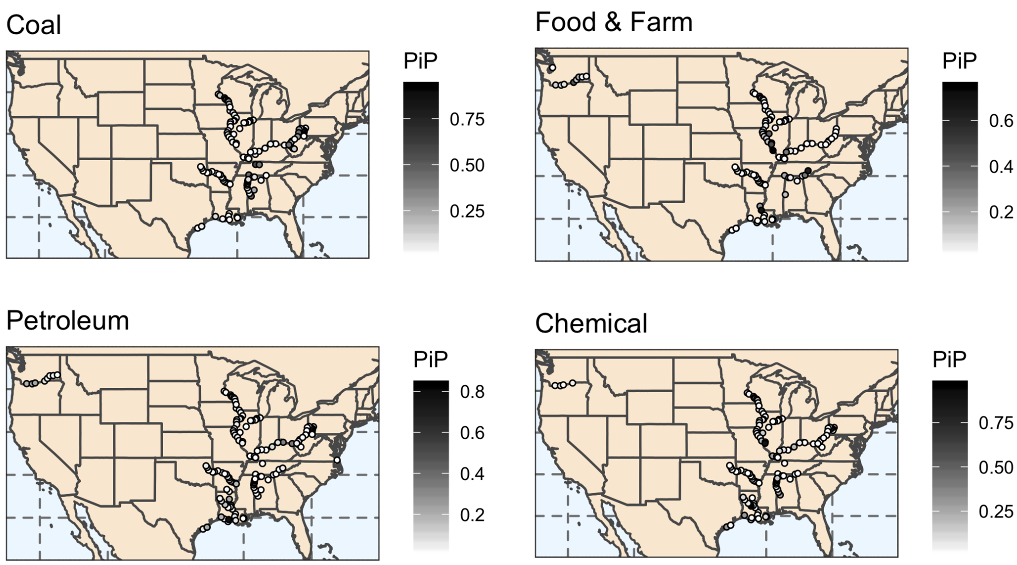


Figure A.III.1
Rail Map for Class I Railroads

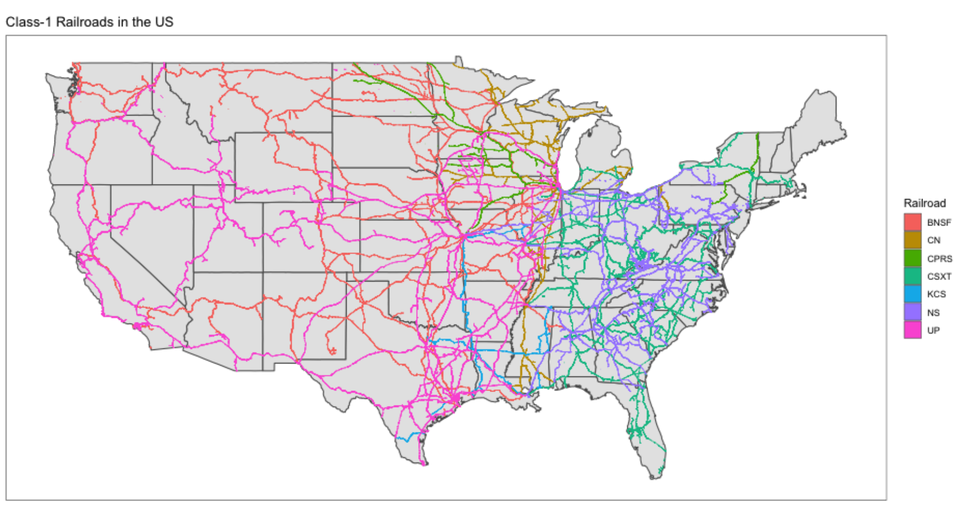
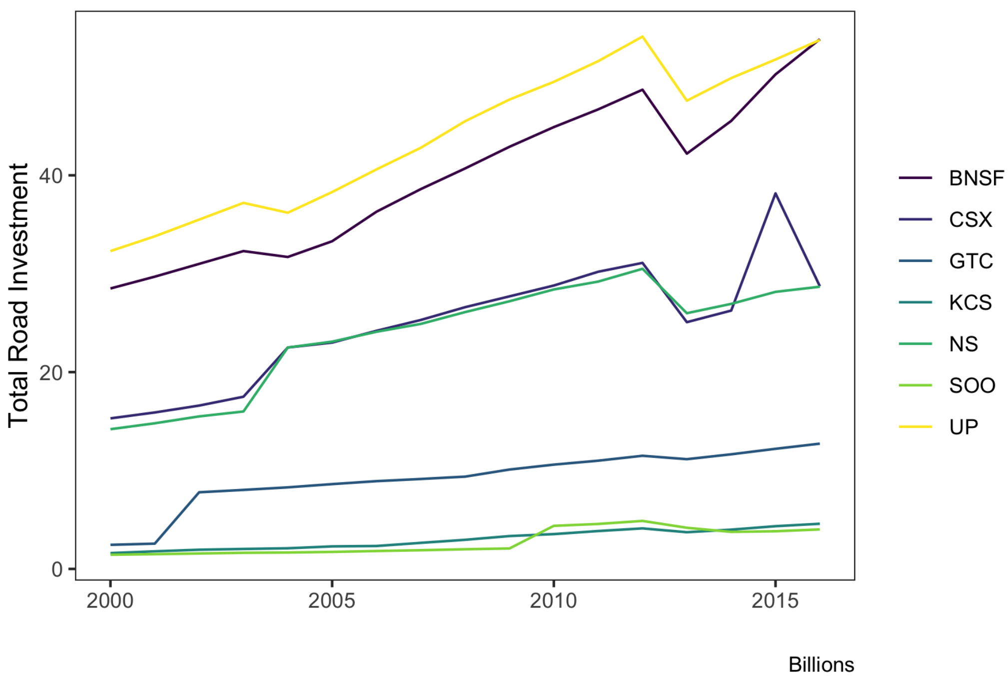


Figure A.III.2
Total Road Investment for Class I Railroads



REFERENCES CITED

Anderson, S. and Wilson, W. W. (2005). Spatial modeling in transportation ii: railroad pricing, alternative markets, and capacity constraints.

Armstrong, S. J. (1985). Long-range forecasting. *John Wiley and Sons Inc.*

ASCE (2009). Infrastructure report card. Technical report, American Society of Civil Engineers.

Azar, J., Marinescu, I., and Steinbaum, M. I. (2017). Labor market concentration. Working Paper 24147, National Bureau of Economic Research.

Azar, J. A., Marinescu, I., Steinbaum, M. I., and Taska, B. (2018). Concentration in us labor markets: Evidence from online vacancy data. Working Paper 24395, National Bureau of Economic Research.

Babcok, M. and Lu, X. (2002). Forecasting inland waterway grain traffic. *Transportation Research Part E: Logistics and Transportation Review*, 38:65–74.

Baumol, W., Panzar, J. C., and Willig, R. D. (1983). Contestable markets: An uprising in the theory of industry structure: Reply. *American Economic Review*, 73(3):491–96.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890.

Bitzan, J. and Wilson, W. (2007). Industry costs and consolidation: efficiency gains and mergers in the u.s. railroad industry. *Review of Industrial Organization*, 30(2):81–105.

Bitzan, J. D. (2003). Railroad costs and competition: The implications of introducing competition to railroad networks. *Journal of Transport Economics and Policy*, 37(2):201–225.

Bitzan, J. D. and Wilson, W. W. (2003). Costing individual railroad movements. Technical report, Federal Railroad Administration.

Board, T. R. (2015). Funding and managing the us inland waterways system. Technical report.

Boyer, K. (1977). Minimum rate regulation, modal split sensitivities, and the railroad problem. *Journal of Political Economy*, pages 493–512.

Bresnahan, T. (1981). Departures from marginal cost pricing in the american automobile industry. *Journal of Econometrics*, 17:201–227.

Brown, J. H. (2013). The 'railroad problem' and the interstate commerce act. *Review of Industrial Organization*, 43:7–19.

Brown, R. S., Caves, D. W., and Christensen, L. R. (1979). Modelling the structure of cost and production for multiproduct firms. *Southern Economic Journal*, 46(1):256–273.

Camacho, M. and Perez-Quiros, G. (2010). Introducing the euro-sting: Short-term indicator of euro area growth. *Journal of Applied Econometrics*, 25(4):663–694.

Caves, D., Christensen, L., Tretheway, M., and Windle, R. J. (2002). Network effects and the measurement of returns to scale and density for u.s. railroads. in: Railways.

Caves, D. W., Christensen, L. R., and Swanson, J. A. (1981). Productivity growth, scale economies, and capacity utilization in us railroads, 1955-74. *The American Economic Review*, 71:994–1002.

Chiang, J. S. and Friedlaender, A. F. (1985). Truck Technology and Efficient Market Structure. *The Review of Economics and Statistics*, 67(2):250–258.

Chiang, S. J. W. and Friedlaender, A. F. (1984). Output aggregation, network effects, and the measurement of trucking technology. *The Review of Economics and Statistics*, 66(2):267–276.

Christensen, L. R., Jorgenson, D., and Lau, L. J. (1973). Transcendental logarithmic production frontiers. *The Review of Economics and Statistics*, 55(1):28–45.

Clark, J. (1925). Studies in the Economics of Overhead Costs. *The Economic Journal*, 35(138):245–250.

Cobb, C. W. and Douglas, P. H. (1928). A theory of production. *The American Economic Review*, 18:139–165.

Coublucq, D. (2013). Demand estimation with selection bias: A dynamic game approach with an application to the us railroad industry.

De Loecker, J. and Warzynski, F. (2012). Markups and firm-level export status. *American Economic Review*, 102(6):2437–71.

Eaton, J. and Center, J. (1985). A tale of two markets: The icc's use of product and geographic competition in the assessment of rail market dominance. *Transportation Practitioners' Journal*, 53:16–35.

Faulhaber, G. R. (1975). Cross-subsidization: Pricing in public enterprises. *American Economic Review*, 65(5):966–77.

Faulhaber, G. R. (2005). Cross-subsidy analysis with more than two services. *Journal of Competition Law and Economics*, 1:441–448.

Faulhaber, G. R. (2014). Stand-alone costs - response to comments. Technical report, American Chemistry: Verified Statement.

Fernández, C., Ley, E., and Steel, M. F. (2001). Model uncertainty in cross-country growth regressions. *Journal of Applied Econometrics*, 16:563–576.

Friedlaender, A. F. and Spady, R. H. (1981). Equity, efficiency, and competition in the rail and trucking industries. *Freight Transport Regulation.*

Giannone, D., Reichlin, L., and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4):665–676.

Giusto, A. and Piger, J. (2017). Identifying business cycle turning points in real time with vector quantization. *International Journal of Forecasting*, 33(1):174–184.

Hall, R. E. (1988). The relation between price and marginal cost in u.s. industry. *Journal of Political Economy*, 96(5):921–947.

Harmatuck, D. J. (1981). A motor carrier joint cost function: A flexible functional form with activity prices. *Journal of Transport Economics*, 15:135–153.

Harris, R. G. (1977). Economies of traffic density in the rail freight industry. *Bell Journal of Economics*, 8:556–563.

ICC, I. C. C. (2016). Determinant of market dominance in rail rate proceedings. https://www.govinfo.gov/content/pkg/USCODE-2017-title49/html/USCODE-2017-title49-subtitleIV-partA-chap107-subchapI-sec10707.htm.

Ivaldi, M. and McCullough, G. (2007). Railroad pricing and revenue-to-cost margins in the post-staggers era. *Research in Transportation Economics*, 20:153–178.

JOC (2016). Class i railroads. https://www.joc.com/rail-intermodal/class-i-railroads.

Keeler, T. E. (1983). Railroads, freight, and public policy. *The Brookings Institute.*

Koop, G. (2003). Bayesian econometrics. *John Wiley and Sons Inc.*, pages 265–280.

Laurits R. Christensen Associates, I. (2009). A study of competition in the u.s. freight railroad industry and analysis of proposals that might enhance competition. Technical report, Surface Transportation Board.

Ley, E. and Steel, M. F. J. (2009). On the effect of prior assumptions in bayesian model averaging with applications to growth regression. *Journal of Applied Econometrics*, 24(4):651–674.

Loecker, J. D., Eeckhout, J., and Unger, G. (2019). The rise of market power and the macroeconomic implications.

Lorenz, M. O. (1916). Cost and Value of Service in Railroad Rate-Making. *The Quarterly Journal of Economics*, 30(2):205–232.

MacDonald, J. M. (1987). Competition and rail rates for the shipment of corn, soybeans, and wheat. *The RAND Journal of Economics*, 18(1):151–163.

MacDonald, J. M. and Cavalluzzo, L. C. (1996). Railroad deregulation: Pricing reforms, shipper responses, and the effects on labor. *ILR Review*, 50(1):80–91.

Madigan, D. and York, J. (1993). Bayesian graphical models for discrete data. *Department of Statistics, University of Washington*, Technical Report 259.

McKenzie, T. K. and Wilson, W. W. (2016). Markups and scale elasticities for differentiated railroad networks.

Miller, G. H. (1954). Origins of the iowa granger law. *The Mississippi Valley Historical Review*, pages 657–680.

National Academies of Sciences, N. (2015). Modernizing freight rail regulation. Technical report.

Pittman, R. (2010). Against the stand-alone-cost test in u.s. freight rail regulation. *Journal of Regulatory Economics*, 38:313–326.

Rhodes, G. F. and Westbrook, M. D. (1986). Econometric analysis of costing system components in rail rate regulation. *Journal of Business & Economic Statistics*, (4):289–303.

Schmalensee, R. (2012). On a level with dentists? reflections on the evolution of industrial organization. *Review of Industrial Organization.*

Schmalensee, R. L. and Wilson, W. W. (2016). Modernizing u.s. freight rail regulation. *Review of Industrial Organization*, 49:135–159.

Spady, R. H. (1986). Using indexed quadratic cost functions to model network technologies. page 121136.

Spady, R. H. and Friedlaender, A. F. (1978). Hedonic cost functions for the regulated trucking industry. *Bell Journal of Economics*, 9(1):159–179.

STB (2019a). Rail rate cases. `https://prod.stb.gov/wp-content/uploads/Rate-Case-List-11-19-2019.pdf`.

STB, R. R. T. F. (2019b). Report and recommendations. Technical report.

STB, S. T. B. (2011). Position paper on the uniform rail costing system. Technical report.

STB, S. T. B. (2016a). Railroad cost program. https://www.stb.gov/stb/docs/URCS/URCS

STB, S. T. B. (2016b). Uniform rail costing system. https://prod.stb.gov/reports-data/uniform-rail-costing-system/.

STB Ex Parte No 646, S. T. B. (2007). Simplified standards for rail rate cases.

STB Ex Parte No 756, S. T. B. (2019). Market dominance streamlined approach: proposed rules.

STB Ex Parte No 756, S. T. B. (2020). Market dominance streamlined approach.

Tang, X. (2001). Time series forecasting of quarterly barge grain tonnage on the mcclellan-kerr arkansas river navigation system. *Journal of Transportation Research Forum*, 43:91–108.

Thoma, M. A. and Wilson, W. W. (2004). Long-run forecasts of river traffic on the inland waterway system. Technical report.

Thoma, M. A. and Wilson, W. W. (2004a). Market adjustments over transportation networks: a time series analysis of grain movements on the inland waterway system. Technical report.

Thoma, M. A. and Wilson, W. W. (2005). Leading transportation indicators: forecasting waterborne commerce statistics using lock performance data. *Journal of Transportation Research Forum*, 44.

Tye, W. B. (1986). Stand-alone costs as an indicator of market dominance and rate reasonableness under the staggers rail act. *International Journal of Transport Economics*, 13:21–40.

Walters, A. A. (1963). Production and cost functions: an econometric survey. *Econometrica*, 31.

Wilson, W. and Wolak, F. (2016). Freight rail costing and regulation: The uniform rail costing system. *Review of Industrial Organization*, 49.

Wilson, W. W. (1996). Legislated market dominance in railroad markets. *Research in Transportation Economics*, 4:49 – 67.

Wilson, W. W. (1997). Cost savings and productivity gains in the railroad industry. *Journal of Regulatory Economics*, 11(1):21–41.

Wilson, W. W. and Burton, M. (1994). Regulation and deregulation of railroad rates.

Wilson, W. W. and Train, K. (2007). Spatially generated transportation demands.

Wilson, W. W. and Wolak, F. A. (2020). Regulation by price benchmarks in the railroad industry. *National Bureau of Economic Research.*

Winston, C. (1985). Conceptual developments in the economics of transportation: an interpretive survey. *Journal of Economic Literature*, 23:57–94.

Wolfe, K. E. (2004). The carload waybill statistics: A content analysis. *Transportation Research Forum Proceedings*.