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BENCHMARK REGULATION OF MULTIPRODUCT FIRMS:
AN APPLICATION TO THE RAIL INDUSTRY

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ABSTRACT

A number of formerly regulated multiproduct industries have a transitional or permanent residual regulatory mandate to protect consumers from "excessive" prices. The legislation that deregulated most rail rates contains a statutory mandate for the regulator to protect shippers from "excessive" prices. Fulfilling this mandate has been challenging because of the cost and administrative burden to shippers in obtaining regulatory relief. Moreover, as argued by Wilson and Wolak (2016), the existing rate relief mechanism is based on a cost concept that does not reflect the actual incremental cost of a shipment and it does not adequately address the question of what constitutes an "excessive" rate for a multiproduct firm with significant common costs. This paper analyzes a benchmark price approach to identifying "excessive" prices in multiproduct industries subject to residual price regulation. Our empirical analyses demonstrate how the mechanism can be used to fulfill the statutory mandate to protect shippers from "excessive" prices at substantially lower cost, with less administrative burden, and without significant adverse consequences for the long-term financial viability of the railroads.

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1. Introduction

A number of formerly regulated multiproduct industries have a transitional or permanent residual regulatory mandate to protect consumers from "excessive" prices. The Federal Energy Regulatory Commission (FERC) is required to ensure that all wholesale electricity prices are "just and and reasonable" and "not unduly discriminatory or preferential," even in parts of the United States with bid-based short-term markets for wholesale electricity. FERC has a similar regulatory mandate for natural gas transportation despite the fact that prices for most natural gas movements are set through bilateral negotiations between the pipeline owner and purchaser of wholesale natural gas. In the aftermath of the Airline Deregulation Act of 1978, the Civil Aeronautics Board (CAB) had a transitional mandate to ensure that airfares were not "unjust and unreasonable." The Staggers Act of 1980, which partially deregulated the railroad industry, imposes a regulatory mandate on the Surface Transportation Board (STB), the industry regulator that replaced the Interstate Commerce Commission (ICC), to protect captive shippers from excessive prices.

These regulatory mandates have proven challenging to enforce to the satisfaction of the parties involved because of the conceptual difficulty in defining a "just and reasonable" price for a multiproduct firm with substantial economies to scope in production. Gaskins (2008) argues that this residual regulatory challenge in the railroad industry "still has not been solved to everyone's satisfaction after 150 years of effort." (Gaskins (2008), p. 1). The essential challenge is that a railroad provides thousands of varieties of shipments, depending on the product and distance shipped, and both the incremental cost of a shipment and marginal cost of shipping an additional ton exclude the vast majority of the railroad's total cost of production.[1] This implies that setting each shipment price equal to either the average incremental cost of the shipment or the marginal cost of shipping an additional ton of that product would not recover sufficient revenue for the railroad to cover its annual costs.

Consequently, in order to recover its total cost of production, the railroad must charge prices above the average incremental cost and the marginal cost of shipping an additional ton for a substantial fraction, if not all, of its shipments. A major goal of the Staggers Act was to grant railroads the freedom to do this, subject to protecting captive shippers from "excessive" prices. The large number of products sold by railroads and the large share of common costs in the railroad's total cost of production imply that even if the railroad's multiproduct cost function was known with certainty, this would not make the job of setting the threshold for an excessive price any easier. As Wilson and Wolak (2016) note, it would only change the regulator's problem from one of determining the value of an excessive price

[1] Costs not caused by a movement or moving an additional ton include the cost of the track, rolling stock, management salaries and benefits, and the vast majority of labor costs.

a shipment to determining the value of an excessive markup over the average incremental cost or marginal cost of a shipment.

The total welfare-maximizing Ramsey-pricing solution of setting the markup over marginal cost for each shipment proportional to the inverse of the elasticity of the demand for the shipment flies in the face of Staggers Act mandate to protect captive shippers. By definition, captive shippers have no other economically viable alternative but the railroad for their shipment and for that reason have a small elasticity of demand for the shipment. This logic rules out a solution that places a significant burden for common cost recovery on captive shippers, as would be the case under Ramsey pricing.[2]

This paper analyzes an alternative approach to determining whether the price charged by multiproduct firm is "excessive" that does not require knowledge of the multiproduct firm's cost function or the elasticity of demand of individual products. Our methodology relies on a set of circumstances that is increasingly prevalent in many formerly regulated industries, the existence of a large sample of "competitive prices" for products along with the observable characteristics of each of these products. We use this sample to nonparametrically estimate the conditional distribution of competitive prices given product characteristics and then use this conditional distribution to construct a benchmark price based on the observable characteristics of a shipment suspected of having an "excessive" price. If the actual price exceeds this benchmark price, then price of the shipment could be deemed "excessive" and therefore worthy of further regulatory scrutiny.

There are two important considerations in setting the value of a benchmark price for a shipment. First is the probability of false positives–competitive prices that are incorrectly found to exceed the benchmark. Second is the possibility of false negatives–non-competitive prices that are incorrectly found not to exceed the benchmark price. We investigate this issue with a Monte Carlo study where we first estimate the conditional distribution of competitive prices given shipment characteristics on data simulated from "competitive markets" and then apply our competitive benchmark methodology using this estimated distributed to data simulated from a mixture of "competitive and non-competitive markets."

Similar to the case of statistical hypothesis testing, a rule for setting the benchmark price that minimizes the sum of squares of misclassification errors argues in favor of approach that requires overwhelming statistical evidence against a price being the result of a competitive market before it is deemed "excessive." Our Monte Carlo results finds that setting the value of the benchmark price between the upper 5 percent and upper 1 percent of the conditional

[2]For the case of zero cross-price elasticities of demand for the products sold by the multiproduct firm, Ramsey pricing implies setting the highest markups over marginal cost for products with the smallest (in absolute value) own-price elasticity of demand. This logic implies that captive shippers would face the highest markups over marginal cost under Ramsey pricing.

distribution of competitive prices given the shipment characteristics minimizes the sum of squared misclassification errors for range of distributions of non-competitive shipment prices.

Another important consideration in the design of our approach is the revenue impacts of resetting shipment prices that violate the competitive benchmark at or below the competitive benchmark price. If violations of the competitive benchmark occur too frequently and if the mitigated shipment price is set too low then then there is a risk that this may cause a railroad that is revenue adequate–it is earning sufficient revenues to recover its total cost of production–to become revenue inadequate. Using the choice of the benchmark price recommended by our Monte Carlo analysis, we explore the impact of different choices for the mitigated or "reasonable" shipment price in the event that an actual price violates our competitive benchmark using actual data from the STB's Waybill sample for four broad classes of shipments: (1) petroleum products, (2) agricultural products, (3) coal, and (4) chemical products.

In all cases, we find that for our choice of the competitive benchmark price, re-setting the price charged equal to any of our three choice for a "reasonable" price for the shipment has a very small percentage impact of the railroad's aggregate revenue.[3] However, for all of our choices of the "reasonable" price, we find that the average value of the difference in prices between the actual non-competitive price and the "reasonable" price is a substantial percentage of the average value of the non-competitive price, which is consistent with our procedure providing significant rate relief to shipper facing prices that our procedure deems are "excessive."

The remainder of paper first summarizes the pre- and post-Staggers Act of 1980 regulatory framework governing the railroad industry. This section summarizes the inefficiencies in the current approach to regulating excessive prices charged to captive shippers and why we believe our competitive benchmark pricing approach helps to overcome these shortcomings. Section III outlines our approach to estimating the conditional distribution of competitive prices given shipment characteristics. Section IV presents the Monte Carlo study we use to compare methodologies for computing the value of the competitive benchmark price from the conditional distribution of competitive prices given product and shipment characteristics. This section then reports on the results of applying our methodology to actual data from the STB's Waybill sample for four broad classes of shipments in order to assess the impact on annual railroad revenues of different approaches to re-setting an "excessive" shipment price. Section V discusses possible uses for our benchmark pricing mechanism in carrying

[3]A less conservative approach to setting the value of the benchmark price, at for example the conditional median price for the observed shipment characteristics, will lead to many more prices being deemed "excessive" and larger revenue losses from re-setting the actual price to this benchmark price level.

out the STB's statutory mandate to protect captive shippers from excessive prices. Section VI summarizes our results and proposes directions for future research.

II. A Brief History of Railroad Regulation

The history of regulatory oversight of railroad industry since the inception of the Interstate Commerce Commission (ICC) in 1887 can be divided into the pre-Staggers Act period when prices and entry into and exit from railroad sector were regulated by the ICC and the post-Staggers Act period when railroad price regulation and entry and exit regulation were largely eliminated. Residual regulation of these functions was conducted by ICC until 1995, when it was eliminated by the ICC Sunset Act. This act also created the Surface Transportation Board (STB) which currently carries out these functions. For both the pre- and post-Staggers regimes we highlight the challenges faced by the railroad sector and its regulatory process. This section concludes with a discussion of why we believe our price benchmark approach to rate regulation could reduce the cost and improve the effectiveness of the STB's current approach to residual price regulation.

II.1. Pre-Staggers Act Railroad Regulation

Prior to the passage of the Staggers Act, rates for all railroad shipments were subject to approval by the ICC.[4] Rate proposals were typically provided by rate bureaus composed of railroad staff that operated cooperatively with antitrust immunity. The ICC would then review these rate proposals and frequently prohibited their implementation or significantly reduced them before they were allowed to be implemented. As Stone (1991) notes, rate reductions to respond to competition from other modes of transportation were often blocked.

This regulatory structure did not encourage efficient operation of the rail network or maximize the revenues earned by the railroads. By the late 1970s, the railroad industry was on the brink of financial collapse, and many individual railroads were bankrupt. It was widely held that the regulatory structure that existed at the time impeded the ability of railroads to meet new forms of competition and impeded innovation in the industry.[5]

The Railroad Revitalization and Regulatory Reform Act of 1976 (4R Act) and the Staggers Rail Act of 1980 provided for significantly reduced federal regulatory oversight of the railroads. This legislation introduced new mechanisms governing the regulation of rates, allowed confidential contracts between railroads and shippers at negotiated rates, and eased impediments to rail line abandonment and to mergers.

II.2. Post-Staggers Act Railroad Regulation

The 4-R Act and Staggers Act placed a greater emphasis on market forces to discipline

[4] There is voluminous literature on railroad regulatory policy. Keeler (1983) provides a comprehensive survey.

[5] See, for example, Keeler (1983), Gallamore and Meyer (2014) and many others for the factors leading to regulatory reform.

rates. The effects of these legislative changes on the railroad industry have been dramatic, with substantial decreases in costs, rates, and the size of the rail network as well as a tremendous consolidation of firms.[6]

The legislation anticipated the need to protect shippers that do not have an economically viable alternative for a shipment. It established the notion of market dominance to protect these so-called captive shippers from "excessive" rates. The STB has the jurisdiction to consider the reasonableness of a rate only if there is a finding that the railroad is market dominant over the movement.

Market dominance is defined as the absence of effective competition from other railroads or modes of transportation (49 USC §10707). A rate is automatically considered reasonable if the revenue the railroad receives (R) it does not exceed 180 percent of its "variable cost," (VC) as determined by the Surface Transportation Board (STB) (49 USC §10707(d)(1)(A)). If a disputed rate fails the R/VC ¡ 180 percent test and is found to be in a market lacking effective competition, the STB can rule on whether the rate is reasonable.[7] To determine the "variable cost" of a shipment, the legislation mandated the existence of a railroad costing methodology to construct this "variable cost." After years of development the Uniform Rail Costing System (URCS) was adopted in 1989, replacing Rail Form A which had been used since 1939. If STB finds the rate to be unreasonable, it must order the railroad to compensate the shipper for overpayments, and it may prescribe the maximum rate the railroad can charge for future movements (49 USC §11704(b), §10704(a)(1).)

Until recently, rate reasonableness cases had to be initiated by the shipper.[8] That is, rates would be set and the regulatory process would begin with a challenge by a shipper after the rate was set. An aggrieved shipper then must have a rate greater than 180 percent of the URCS "variable costs" for the shipment and the regulatory authority find a lack of effective competition before the reasonableness of the rate could be considered.

Currently, shippers can bring rate cases under three different methods including a Stand-Alone Cost (SAC), which was introduced by the ICC in 1985, and two simplified procedures introduced by the STB in 1997, the Simplified SAC and the Three-Benchmark.[9] SAC was introduced in 1985 (Coal Rate Guidelines, Nationwide. 1985 [1 ICC.2d 520, 1985 WL 56819

[6] These changes are documented in McFarland (1989), Barnekov and Kliet (1990), Berndt et al. (1993), Vellturo et al. (1992), Burton (1993), Wilson (1994; 1997), MacDonald and Cavalluzzo (1996), Grimm and Winston (2000), Ellig (2002), Bitzan and Keeler (2003), Bitzan and Wilson (2007), Winston et al. (2010), Schmalensee and Wilson (2016).

[7] See Eaton and Center (1986) and Wilson (1996) for more details on process used to determine market dominance.

[8] The Surface Transportation Board Reauthorization Act of 2015 now authorizes the Board to investigate on its own initiative (S.808, Section 11).

[9] Wilson and Wolak (2016) provide a review of these procedures.

(ICC)). In a SAC case, the stand-alone cost of a hypothetical railroad providing that shipment is used to establish an upper bound on the rate that is deemed reasonable for the shipment.

The time and effort required to make a SAC claim against a railroad are substantial. The process of determining the stand-along cost for a hypothetical railroad providing the shipment is extremely complex with ample room for disagreement between parties about the many assumptions underlying the calculation. Each of these points of disagreement must be litigated at the STB, which makes the entire process both expensive and time-consuming. The STB (2013) estimates the costs of pursuing a SAC case can exceed \$5 million.[10]

Cost and complexity of SAC rate cases led to number of legislative and policy changes by the STB to reduce the time and cost of filing for rate relief. In the ICC Termination Act of 1995, Congress ordered the STB to develop expedited procedures for resolving disputes. In response, the STB introduced the Simplified SAC and the Three-Benchmark standards in 1997. Each expedited procedure limits the evidence that parties can submit and sets a time limit for decisions.[11] These simplified procedures also limit the amount of refunds a shipper can obtain from "excessive" prices.

To implement the first stage of the excessive rate test, the "variable cost" of the shipment under consideration must be calculated, and the legislation mandates that the STB have a costing methodology.[12] The ICC had used Rail Form A, an accounting-based cost allocation system for railroad services and activities, since 1939. Under the Staggers Act regulatory reforms, the ICC was charged with developing an updated method to determine "economically accurate railroad costs directly and indirectly associated with particular movements of goods, including the variable costs associated with particular movements."[13] To comply, the ICC developed the Uniform Railroad Costing System (URCS), which was adopted in 1989 and shares a methodological approach with earlier cost accounting schemes and remains in use today.

Wilson and Wolak (2016) examined theoretical and empirical validity of URCS methodology for computing the "variable cost" of a shipment. They argue that it is an *ad hoc* cost allocation methodology that is inconsistent with the economic theory of multiproduct costing. Using shipment prices from the STB's Waybill sample, the authors find many instances of railroads providing a shipment at a price that is less than the URCS "variable cost." This "irrational" behavior by railroads implied by the URCS costing methodology

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

[11] See Pittman (2010) and Wilson and Wolak (2016) for more complete discussions of these procedures.

[12] The Staggers Rail Act, §10705a(m)(1), required ICC to determine variable costs by using its Rail Form A costing method or to adopt an alternative method.

[13] Cost accounting principles in Title III, Section 301, §11162 of the Staggers Rail Act of 1980.

and its inconsistency with the economic theory of multiproduct costing argues against the use of the URCS "variable cost" in determining excessive rates. Wilson and Wolak (2016) conclude that URCS costs do not meet the law's requirement for economically accurate shipments costs, and are therefore have little relevance to the price charged for a given unit of traffic, contrary to their use in the law's R/VC formula. STB's own Railroad–Shipper Transportation Advisory Council has referred to URCS as "an outdated and inadequate costing system."[14]

Although there are inefficiencies induced by this costing system, it is mandated by legislation. In addition to being used in screening traffic for rate relief eligibility according to the R/VC formula, URCS is used in subsequent procedures to determine market dominance, to make assessments of whether a challenged rate is reasonable, and, if necessary, to prescribe the maximum tariff rate a railroad may charge. URCS is also used in measuring avoidable costs when a railroad applies to abandon a line and in calculating compensation fees for mandated access (STB 2010, 6–8). It is also used by others to judge levels of market power and trends in the industry.[15].

Even if the STB had access to perfect measures of the incremental cost for all possible shipments a railroad could provide, this information would not get it any closer to determining what is an "excessive" price or what a "reasonable" price is for a shipment because of the substantial fixed and common costs associated with providing rail service. Financial viability of a railroad requires it to charge prices in excess of the incremental and marginal cost of a shipment for as many shipments as possible in order to recover these fixed and common costs. With perfect estimates of the incremental and marginal cost of a shipment, the STB faces the equally challenging tasks of first determining what an "excessive" markup over the incremental cost or marginal cost of a shipment is and then what is a "reasonable" markup over these cost measures.

Our price benchmark approach explicitly addresses these challenges by using information from shipments subject to effective competition to determine what is an "excessive" price for a shipment and what is a "reasonable" price for a shipment. Our price benchmark approach would also be significantly less costly for shippers both in terms of time and legal expense.

[14] `http://www.stb.dot.gov/stb/docs/RSTAC/RSTAC{%}20URCS{%}20White{%}20Paper\{%}20on{%}20URCS{%}20November{%}2022.pdf.`

[15] For example, in 2006 the U.S. Government Accountability Office (GAO) examined trends in shipments having rates with various R/VC percentages to determine whether railroads were obtaining and exercising more market power over time (GAO 2006). In finding that the share of traffic having R/VCs above 180 percent had dropped from 1985 to 2004, GAO surmised that the market power of railroads had been declining. Coincidental with these findings, however, GAO found that the amount of traffic having R/VCs exceeding 300 percent had increased from 4 to 6 percent, which caused the agency to question whether railroads were becoming more effective in exploiting market power when they possessed it (GAO 2006, 43)

It also does not involve the use of the URCS costing methodology. It would make use of the fact that an increasing number of shipments are occurring at negotiated rates where the railroad faces effective competition for the shipment.

Prices for shipments from effectively "competitive" markets, are used estimate the conditional distribution of shipment prices given observable chacteristics of the shipment that account for differences in shipment costs, competitive conditions, and the commodity shipped. We then use this estimated conditional distribution to compute a price benchmark for a potentially "uncompetitive" shipment based on its observable characteristics. A percentile of the competitive price conditional distribution is the benchmark relative to which the actual rate is compared to identify non-competitive rates. This approach can be applied to all markets, railroads, and commodities utilizing data that are easily obtained and/or collected by the STB, primarily through its Waybill sample.

The maintained assumption behind our approach is that the conditional distribution of prices given a broad class of product and shipment characteristics estimated from the sample of competitive shipments provides provides a valid estimate of the distribution of "competitive" prices given any vector of observed shipment characteristics. The STB's relative preference for reducing the probability of falsely finding that a competitive shipment price is not competitive versus reducing the probability of failing to reject that a non-competitive shipment price is competitive, determines the percentile of the conditional distribution of competitive prices that becomes the price benchmark for determining if the observed price for the shipment is excessive. As we demonstrate below, this process is very similar to choosing the critical value for a statistical hypothesis test.

III. Estimating the Competitive Price Conditional Distribution

This section describes our procedure for estimating the distribution of the "competitive" price for a shipment conditional on the product and shipment characteristics. This conditional distribution is the essential input for computing the competitive benchmark price used to determine whether an actual shipment price is "excessive." Our approach is completely nonparametric and only relies on the existence a random sample of "competitive" shipment prices and product and shipment characteristics, such as the one available from the Waybill Sample compiled each year by the STB.

The remainder of this section first summarizes our methodology for estimating the conditional distribution of the competitive price given the characteristics of the shipment.[16] We then briefly describe the Waybill data sample and how it is used to estimate this conditional

[16] Appendix A describes the technical details of our methodology. An important step in the estimation process described in Appendix A is the selection of the bandwidth for the kernel regression estimate of this conditional distribution.

distribution. Finally, we describe how the estimation process can be automated to update this conditional distribution each year with the new Waybill Sample.

III.1. Estimation Procedure

We want to estimate $F(y|X)$, the cdf of the conditional distribution of the y, the shipment price, given a vector X of J variables, the vector of product and shipment characteristics, using $i = 1, \ldots, N$ observations.[17] We utilize the Nadaraya-Watson kernel regression estimator of $F(y|X)$ that accounts for stratified sampling shipments:

$$\begin{aligned}\hat{F}(y|X,a) &= \frac{\frac{1}{N}\sum_{i=1}^{N}(EF_i)K_a(X-X_i)\mathbf{I}\big(y_i \leq y\big)}{\frac{1}{N}\sum_{i=1}^{N}(EF_i)K_a(X-X_i)} \\ &= \frac{\sum_{i=1}^{N}(EF_i)K_a(X-X_i)\mathbf{I}\big(y_i \leq y\big)}{\sum_{i=1}^{N}(EF_i)K_a(X-X_i)}\end{aligned}$$

where $\mathbf{I}(expression)$ is 1 if $expression$ is true, and 0 otherwise. EF_i is the expansion factor associated with the i^{th} observation giving the number of shipments in the population of annual shipments that has the same observable characteristics X as this shipment.

Kernel regression is a nonparametric method for estimating the conditional mean function of one element of a random vector, y, given the remaining elements of that random vector, X.[18] $\hat{F}(y|X,a)$ is a consistent estimate of the population conditional distribution of y given X that accounts for the fact that a stratified random sample is used to estimate $F(y|X)$.

Given a sample of "competitive" shipment prices, associated product and shipment characteristics and expansion factors, computing the value of $\hat{F}(y|X)$ for a potentially non-competitive shipment price and product and shipment characteristics pair $(y, X')'$ requires computing the N-term summation shown above. Consequently, once the vector of smoothing parameters a described in Appendix A has been chosen, the process of updating $\hat{F}(y|X)$ with new data is straightforward to automate. Appendix A describes how the process choosing a can be automated as well, although if the new observations are similar to the existing data used to compute $\hat{F}(y|X)$, updating the value of a may be unnecessary.

III.2. Data

The STB's Carload Waybill Statistics (CWS) is the primary data source used to estimate the conditional distribution of the competitive price given a shipment's observed character-

[17]The method we use does not involve the smoothing of y. Another method would be to smooth y and get $F(y|X)$ analytically by integrating $f(y|X)$. the conditional density of y given X, over y. We found this, however, to induce more bias into our estimate of the conditional distribution particularly in the tail of the distribution, which we demonstrate is the portion of the price distribution most relevant to computing our competitive benchmark price.

[18]Pagan and Ullah (1999) provide an accessible introduction to this nonparametric conditional mean estimation procedure.

istics. Each year's CWS consists of more than 500,000 randomly sampled shipments with information on revenue, distance, shipment size, and the identity of the railroads that provided the service.

The CWS records also contain codes that can be linked with Oak Ridge National Laboratory (ORNL) Rail Network files to allow shipper and receiver locations to be identified. Specifically, rail station records are identified by a Standard Point Location Code. These identifiers permit mapping of origin and destination stations into the CWS and the assignment of latitude and longitude values to each shipment origin and destination. These data, along with railroad network geographic information system data, were combined to identify locations of stations and shipment origins and destinations and to develop measures of railroad competition.[19]

The data were also used in conjunction with the Port Series[20] data produced by the U.S. Army Corps of Engineers to measure the presence of water competition. The Port Series data indicate the location of ports on U.S. waterways along with the commodities handled by each port.

All rates from the CWS were adjusted to constant 2009 dollar values by using the gross domestic product price deflator available from Federal Reserve Economic Data through the Federal Reserve Bank of Saint Louis.[21]

We use the subsample of the CWS movements that the STB has deemed are competitively provided and therefore exempt from regulatory oversight to estimate the competitive price condition distribution. For all of the products we consider, this subsample is composed of the two classes of movements created by the Staggers Act: (1) exempted traffic and (2) contract movements.[22] At the time Staggers was passed our approach was not feasible in that all rates were subject to regulation. But, Staggers allowed the regulatory authority to exempt traffic from regulation (49 USC §10502) and it allowed the use of confidential contracts which were not subject to regulation. Under partial deregulation, large classes of traffic were exempted by the ICC and the contracts became widely used.

The legislation declared that the new regulatory policy would be to allow "competition and the demand for services to establish reasonable rates for transportation by rail." (49 USC §10101 (1)). Regulators were instructed to be aggressive in fully exempting from any further regulatory control all traffic—truck-competitive traffic being the most obvious—for

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

[20] `http://www.navigationdatacenter.us/ports/ports.htm`.

[21] `http://research.stlouisfed.org/fred2/`.

[22] Other definitions of competitively provided shipments could be used. For example, in an early version of this methodology reported in the National Academies of Sciences report, *Modernizing Freight Rail Regulation* we used exempted traffic and contract shipments with more than one railroad serving the origin or destination or water availability transport availability at the origin or destination.

which regulation was “not needed to protect shippers from the abuse of market power.”[23] Once it designated a class of traffic ”exempt,” the ICC would have no longer have control over the rates charged to shippers or the amount and quality of service made available to them.

For commodities that were not ruled exempt, a critical reform was the law’s legalization of confidential contracts between railroads and shippers. Any shipment moved under contract would be automatically excluded from any further regulation during the life of the contract; railroads would thus be free to tailor their rate and service offerings on a shipper-by-shipper basis.

The ability of a railroad to contract gave it substantial latitude to set rates differentially according to a shipper’s individual circumstances and willingness to pay. Railroads would not only be allowed to compete more aggressively for the newly exempted freight that is inherently competitive with trucks but would also be allowed to set tariff rates for the nonexempt bulk commodities at levels equivalent to the most rail-dependent shipper’s willingness to pay. While shippers with more transportation options would be expected to refuse to pay the higher rate, a railroad could simply negotiate a discounted contract rate with terms tailored to each shipper’s specific situation and willingness to pay. The price-differentiating railroad would now be able to set rates at levels that avoid pricing any profitable traffic flows out of the market.[24]

Exempt traffic and contract shipments were designed to provide the railroads with an the opportunity earn the sufficient revenues for their long-term financial viability. Since the passage of the Staggers Act, the share of total shipments in the CWS designed as ”exempt” or ”contract” has grown continuously, which is major factor in explaining the improved financial condition of Class I railroads. This trend implies that the quality of our competitive shipment price conditional distribution is likely to improve over time.

Nevertheless, shipments that are neither ”exempt” nor ”contract” and therefore subject to the Staggers Act provision to protect captive shippers against excessive shipment rates are likely to continue to exist. Therefore, a mechanism for determining whether a shipment rate is ”excessive” will continue to be necessary. Our competitive benchmark approach provides a low-cost alternative to the current approach to addressing this statutory mandate.

IV. Choosing Competitive Benchmark and ”Reasonable” Prices for a Shipment

[23] 49 USC §10502. Although the exemption provision is not explicit in identifying trucks as the competition of interest, trucks are the only ubiquitous mode, and thus a commodity’s practical capability to be moved by truck became the de facto standard for deciding whether a commodity should be considered inherently competitive and granted a categorical exemption.

[24] Because of the incentive to extract rents but not price traffic out of the market, the efficiency loss from railroads having pricing freedom is expected to be minimal. Indeed, limited deadweight loss was found by Grimm and Winston (2000, p. 65).

Our use of a price benchmark is different from the typical use of this construct in a regulatory proceeding. Price cap regulation typically specifies a maximum price or set of maximum prices that a price-regulated firm is allowed to charge for all of its products. These prices are designed to allow the firm an opportunity to recover its total cost of production through prudent operation. Yardstick regulation determines these maximum prices by using information from a group of "like" firms producing the same product. Again, the resulting price benchmark is used to set the maximum price that the firm can charge for its output.

Our application differs from these uses of a benchmark price because a growing share of shipments are provided at market-determined prices, whereas under price cap and yardstick regulation all of the firm's output is subject to this maximum price regulation. Our price benchmark only determines the level of an "excessive" price for shipments that have not yet been definitively determined to be "competitively" provided.

Setting the value of the "excessive price" for a shipment involves balancing two risks. The first is the risk of incorrectly determining that the observed shipment price is excessive when the shipment price is the result of effective competition and the second is the risk of failing to determine that a truly excessive price is in fact excessive. Because our benchmark price is derived from the conditional distribution of competitive prices given shipment characteristics, we can build on the theory of statistical hypothesis testing to determine the value of the competitive benchmark price. Specifically, our benchmark price is analogous to a critical value for the test of the null hypothesis that a shipment price is competitively determined versus the alternative that it is "excessive."

If this null hypothesis is rejected, this raises the question what this "excessive" price should be reset to. This decision also involves balancing two risks. The first is the risk of setting this price too low and increasing the probability that the railroad does not recover sufficient revenues to cover its total production costs. The second is the risk that setting this price too high does not protect the shipper from excessive pricing. The Staggers Act anticipates this first risk by requiring the STB to make an annual determination of whether each Class I railroad is revenue adequate in the sense of earning sufficient revenues to recover its total cost of production.

This remainder of this section first presents the results of a Monte Carlo experiment to determine the value of the competitive benchmark price that "optimally" balances the risks of failing to reject the hypothesis that a truly excessive price is competitively determined versus the risk of falsely rejecting this null hypothesis for a price that is truly competitively determined. We then use the results of this Monte Carlo study to inform our choice of the value of the competitive benchmark price for our assessment of the impact on annual railroad revenues of various choices of the price that that an actual price is reset to (the "reasonable" price for the shipment) if it determined to be "excessive" using data from four classes of products from the CWS data.

IV.1. Monte Carlo Experiment on the Selection of Benchmark Price

In order to study the impact of the choice the value of the competitive benchmark price on the probability of each type of classification error, we require an environment where we know with certainty whether a shipment price is competitively determined. To do this we assume that a number of hypothetical railroads supply $i = 1, \ldots, N$ shipments, each with demand

$$D_i(p) = Ap^{-\alpha_i}$$

where $\alpha_i = z_i\delta + \eta_i$. The demand shifters, z_{ij}, are assumed to be independent and identically distributed $U(-1, 1)$ random variables. Let $M = 4$ be the number of demand shifters for each good. Define $z_i = (z_{i1}, \ldots, z_{iM})' \in \mathbb{R}^M$ and

$$\delta = (\frac{1}{4}, \ldots, \frac{1}{4})' \in \mathbb{R}^M \quad and \quad \eta_i \sim U(6, 7).$$

The values of the demand shifters, z_{ij}, are selected to yield market prices with "competitive" markups over marginal costs.

For the railroads' cost function, let $C(q_1, q_2, \ldots, q_N) = \sum_{i=1}^{N}[w_i\gamma + \epsilon_i]q_i$, where w_i is a K-dimensional vector cost shifters. Draw the w_{ij} as independent and identically distributed $U(-1, 1)$ random variables. Let $K = 5$ be the number of cost shifters for each good. Define $w_i = (w_{i1}, \ldots, w_{iK})' \in \mathbb{R}^K$ and let $\epsilon_i \sim U(4, 5)$. Set

$$\gamma = (\frac{1}{4}, \ldots, \frac{1}{4})' \in \mathbb{R}^K.$$

Variations in marginal cost are driven by variation in the w_{ij}. This variation in the values of w_{ij} is chosen so that there high price competitive outcomes because of high values of marginal cost.

Assuming the railroads set each shipment price, p_i, to maximize the sum of profits over the N shipments:

$$\pi(p_1, p_2, \ldots, p_N) = \sum_{i=1}^{N} D_i(p_i)p_i \; - \; C(D_1(p_1), D_2(p_2), \ldots, D_N(p_N)),$$

yields prices for each of the $i = 1, 2, \ldots, N$ shipments equal to

$$p_i = \left(\frac{-(z_i\delta + \eta_i)}{-(z_i\delta + \eta_i) + 1}\right)(w_i'\gamma + \epsilon_i) \tag{1}$$

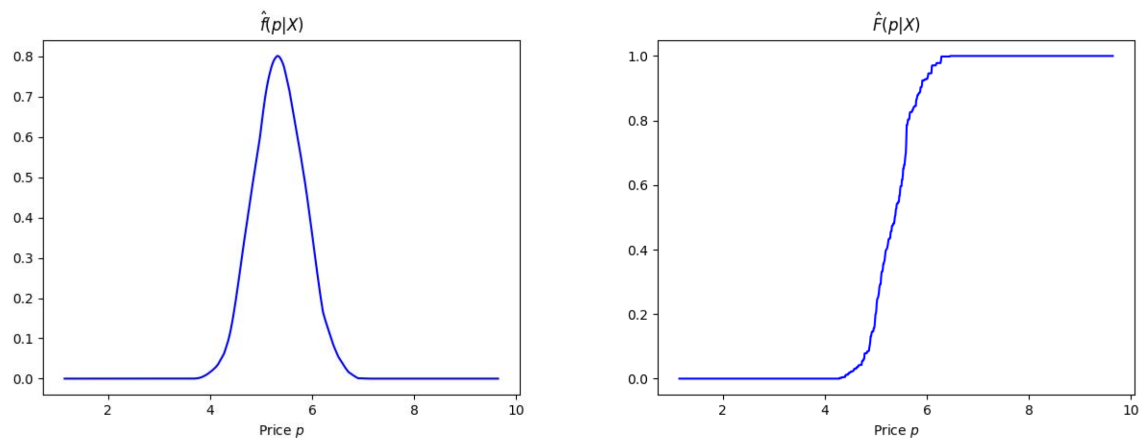
Equation (1) demonstrates that variations in the markups over marginal cost are driven by variation in the values of the z_{ij} and variations in marginal cost are driven by variation in the w_{ij}. The combination of these two observable sources of random variation along with the two unobservable sources of random variation in η_i and ϵ_i produces a conditional distribution of shipment prices given the z_{ij} and w_{ij}.

Translating the variables of this economic model into our notation for the conditional distribution of the competitive price let, $X_i = (z_i, w_i)$, equal the set of conditioning variables and $y_i = p_i$. We then use these N observations of y_i and X_i to estimate the conditional distribution of competitive prices given the shipment characteristics, $\hat{F}(p|X)$, following the procedure described in Section III.

Figure 1 presents the estimated values of $\hat{f}(p|X)$ and $\hat{F}(p|X)$ for $N = 1,000$ observations, for a fixed value of X. Although there is significant variation in prices, p_i, the variation in the markup of price over the marginal cost caused by variation in the values of z_{ij} is within the range of what we consider to be the result of effective competition. The majority of the variation in prices is due to variation in marginal costs caused by variation in the observed cost shifters, w_{ij}, and variation in the unobserved values of η_i and ϵ_i. For this reason, we assume that all of the prices that arise from solving equation (1) are the result of "effective" competition and are therefore truly "competitive."

Figure 1: Conditional Density and Distribution of Competitive Price given X

(a) PDF (b) CDF



Our choice of the benchmark price is equivalent to selecting the value of the percentile of the conditional distribution of competitive prices given shipment characterics beyond which any observed price would be deemed "excessive." Suppose p^* is the price of a potentially "excessive" priced shipment with characteristics X^*. If $1 - \alpha$, for $1 > \alpha > 0$, is the percentile of the distribution of $\hat{F}(p|X)$ beyond which prices are deemed to be excessive, then $PB(\alpha, X^*)$ solves the equation $1-\alpha = F(PB(\alpha, X^*)$. If $p^* > PB(\alpha, X^*)$, then the null hypothesis that the observed shipment price, p^* is "competitive" would be rejected. An equivalent decision rule is $\hat{F}(p^*|X^*) > 1-\alpha$ this null hypothesis would be rejected.

The Monte Carlo samples of truly "competitive" and truly "excessive" prices used to determine the "optimal" value of α are constructed as follows. We repeat the process of drawing observations of $(z_i, w_i, \eta_i, \epsilon_i)$ for $i = 1, 2, \ldots, \mathbf{M}$, and compute p_i using equation (1) for all i. Then, for every k values of the p_i, we compute an "excessive price,' $\tilde{p}_i$ and replace p_i with $\tilde{p}_i$. The processes used to compute these "excessive prices" are described below.

For each $i = 1, 2, \ldots, \mathbf{M}$ in this test sample, define

$$\begin{aligned} I_i &= 1 \ \textit{if observation of } p_i = \tilde{p}_i \\ &= 0 \ \textit{otherwise.} \end{aligned}$$

This indicator variable is equal to 1 if the i^{th} price observation is truly competitive and 0 if this observation is truly non-competitive.

For each (p_i, z_i, w_i) combination in the test sample, we compute $\hat{F}(p_i|z_i, w_i)$ using the competitive price distribution estimated from the $N = 1,000$ competitive price draws. We then find the value of α which minimizes the sum of squared misclassification errors:

$$\sum_{i=1}^{\mathbf{M}} (I_i - \hat{I}_i)^2 \tag{2}$$

where $\hat{I}_i$ is a simple rule where $\hat{I}_i = 1$ if $\hat{F}(p_i, z_i, w_i) > 1-\alpha$, and 0 otherwise. Depending on the value α, the value of $\hat{I}_i$ indicates whether the i^{th} price exceeds the value of $PB(\alpha, X)$, the benchmark price for a shipment with characteristics X and that value of α. Ideally, we would like $\hat{I}_i = I_i$ when $I_i = 1$ and $I_i = 0$, meaning that when the price is truly "competitive" it does not exceed the benchmark price and when it is truly "non-competitive" it does exceed the benchmark price. This would make our objective function equal zero for all observations. Note that both types of misclassification errors, $\hat{I}_i = 0$ when $I_i = 1$ and $\hat{I}_i = 1$ when $I_i = 0$, contribute the same value, 1, to the objective function.

Solving for the value of α that minimizes (2) is the equivalent of finding the competitive benchmark price function, $PB(\alpha, X)$, that minimizes the sum of squared misclassification errors for observations $(y_i, X_i')'$ in our test sample of "competitive" and "uncompetitive" prices.

To compute "excessive" prices in our test sample, we change the distribution of η_i. We let

$$\tilde{p}_i = \left(\frac{-(z_i\delta + \tilde{\eta}_i)}{-(z_i\delta + \tilde{\eta}_i) + 1} \right) (w_i'\gamma + \epsilon_i)$$

where $\tilde{\eta} \sim U(m, n)$. We keep $\eta_i \sim U(6, 7)$ for competitive observations for all scenarios. We alter the distribution of $\tilde{\eta}_i$ starting with a distribution of $\tilde{\eta}_i$ with a support that has the same range but is significantly lower than the support of η. The support of $\tilde{\eta}_i$ has the same range but closer to the support of η_i across the scenarios we consider. The closer the support of $\tilde{\eta}_i$ is to the support of η_i, the more likely it is that our procedure will mistakenly classify "competitive" prices as "excessive" and "excessive" prices as "competitive."

For all of the scenarios, we set $M = 3,000$ and $k = 5$. Second column of Table 1 presents the value of α that minimizes the sum of squared misclassfication errors for each distribution of $\tilde{\eta}_i$ listed in the first column of the table. The third column of the table lists the number of the number of Type I errors (competitive prices classified as "excessive price" observations) and the fourth column the number of Type II errors ("excessive price" observations classified as competitive) for each distribution of $\tilde{\eta}_i$. The final column gives the percentage of the 3,000 test sample observations that are misclassified (the sum of Type I and II errors) for each distribution of $\tilde{\eta}_i$.

We find that as the support of the distribution of $\tilde{\eta}_i$ comes closer to the support of the distribution η_i, the distribution of "excessive" prices is closer to the distribution of "competitive" prices. The percent of observations in our test sample that are misclassified rises. However, even for the case that the supports of $\tilde{\eta}_i$ and η_i are virtually the same, $(5.75, 6.75)$ versus $(6, 7)$, less than 20 percent of the observations in the test sample are misclassified. Finally, for all of the scenarios considered the value of α that minimizes the sum of squared misclassification errors lies in the interval (0.0627,0.0133).

These results demonstrate that if the support of the distribution of competitive prices and the support of the distribution "excessive prices" are closer to together, the smaller is the value of the α that minimizes the sum of the squared misclassification errors. These Monte Carlo results suggest that in practice the value of α is unlikely to be larger than 0.06 and smaller than 0.01.

Figures 2 to 7 contains graphs of the values of $\hat{f}(p|X)$ and $\hat{F}(p|X)$ for all prices in our test samples for each of the six scenarios for the support of $\tilde{\eta}_i$ we consider. The red dots are the truly non-competitive observations and the blue dots are the truly competitive observations. These graphs and Table 1 illustrate that the major cost in terms of misclassification errors as the supports of the distributions of competitive and non-competitive prices come closer is a substantial increase in Type II errors–failing to find that a non-competitive price is "excessive." For all of the scenarios considered, the frequency of Type I errors–concluding that a competitive price is ”excessive” remains very low.

Table 1: Monte Carlo Results

$\tilde{\eta}_i \sim$	α	Type I Error	Type II Error	% Misclassified
$U(3.75, 4.75)$	.0478	34	339	10.2
$U(4, 5)$	.0627	58	365	10.2
$U(4.5, 5.5)$	.0478	34	481	14.9
$U(5, 6)$	.0303	17	553	17.9
$U(5.5, 6.5)$	.0133	2	586	19.5
$U(5.75, 6.75)$	.0133	2	590	19.6

Figure 2: Conditional Distributions with $\eta_i \sim U(6, 7)$ and $\tilde{\eta}_i \sim U(3.75, 4.75)$

(a) PDF

(b) CDF

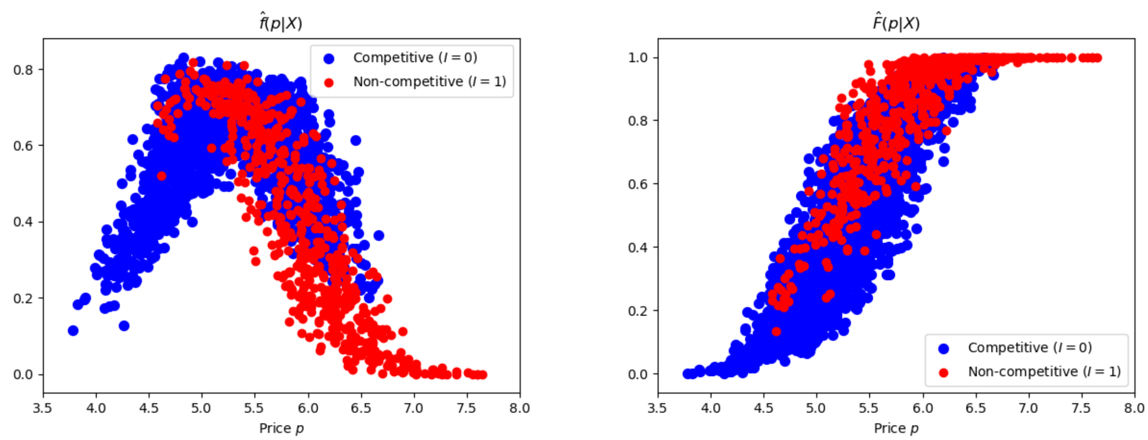


Figure 3: Conditional Distributions with $\eta_i \sim U(6,7)$ and $\tilde{\eta}_i \sim U(4,5)$

(a) PDF (b) CDF

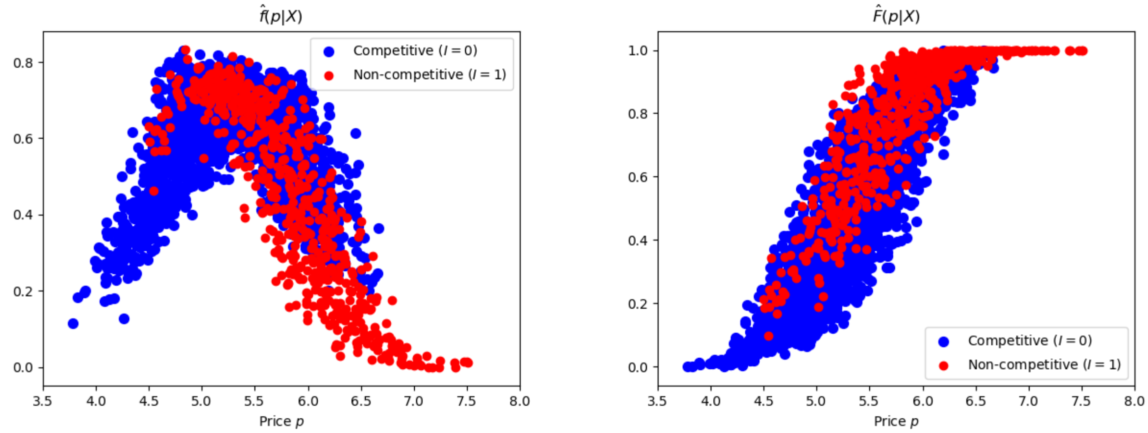


Figure 4: Conditional Distributions with $\eta_i \sim U(6,7)$ and $\tilde{\eta}_i \sim U(4.5,5.5)$

(a) PDF (b) CDF

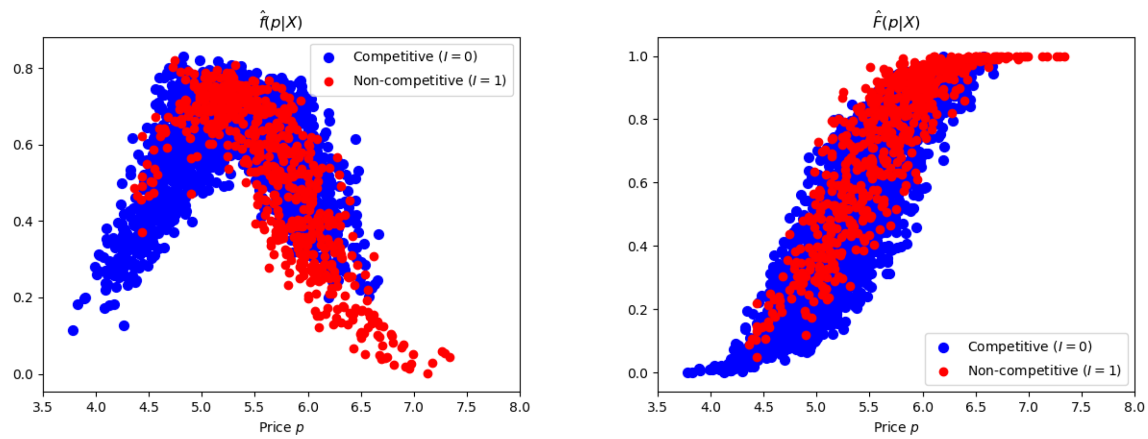


Figure 5: Conditional Distributions with $\eta_i \sim U(6,7)$ and $\tilde{\eta}_i \sim U(5,6)$

(a) PDF (b) CDF

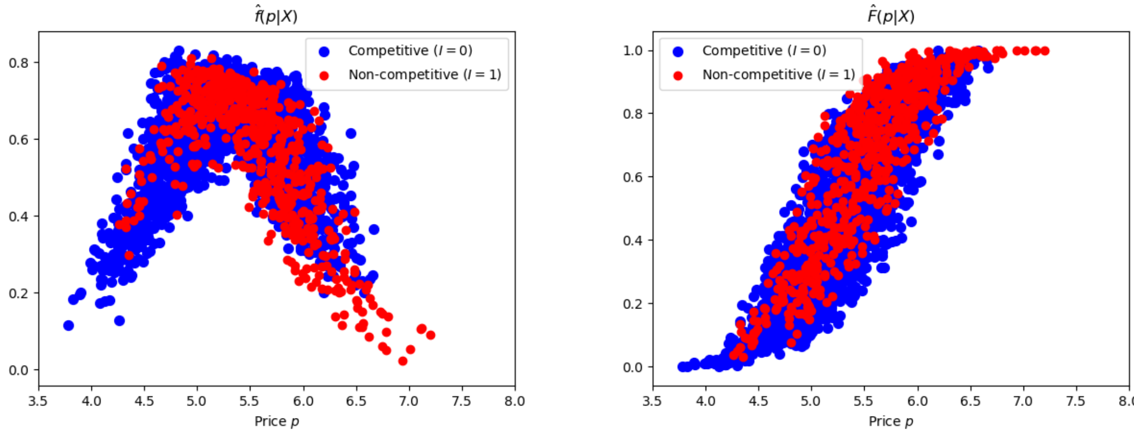


Figure 6: Conditional Distributions with $\eta_i \sim U(6,7)$ and $\tilde{\eta}_i \sim U(5.5,6.5)$

(a) PDF (b) CDF

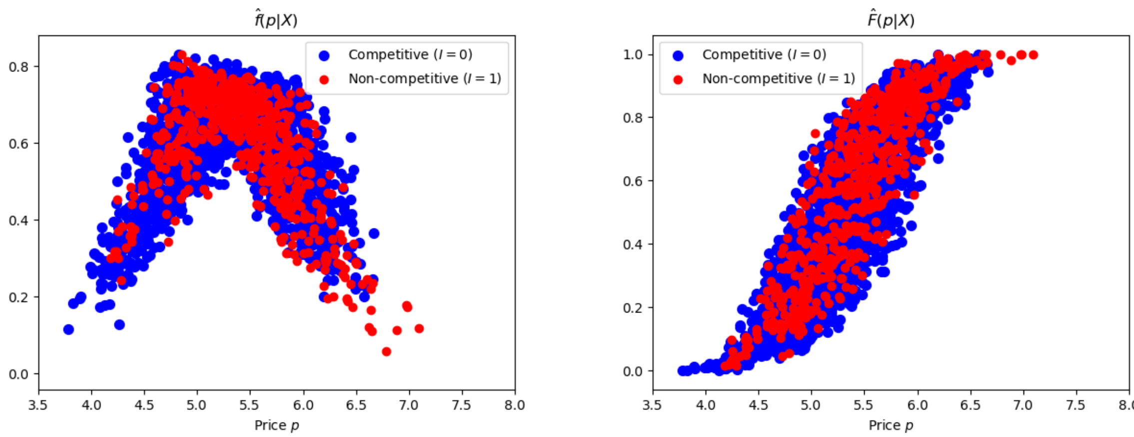
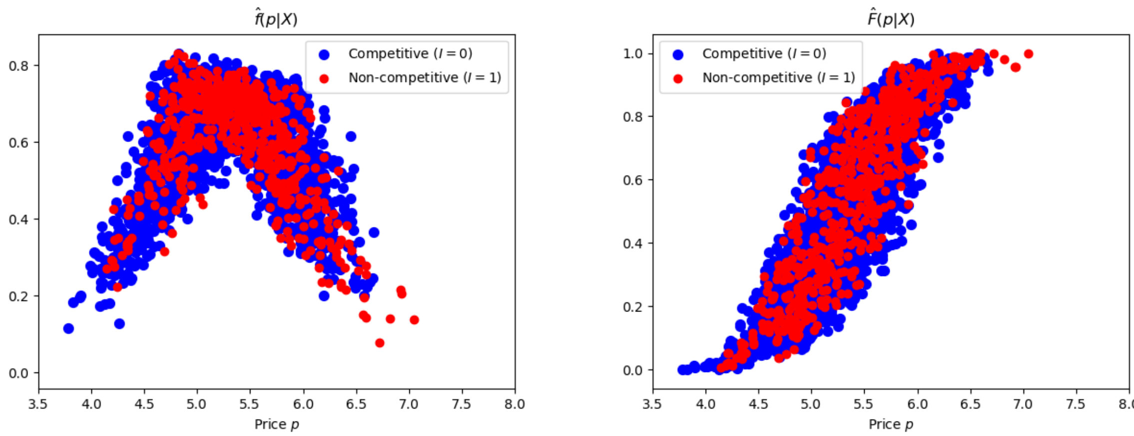


Figure 7: Conditional Distributions with $\eta_i \sim U(6,7)$ and $\tilde{\eta}_i \sim U(5.75, 6.75)$

(a) PDF (b) CDF



IV. Determining a "Reasonable Price" for a Shipment

Using the above results, we now implement our competitive benchmark pricing procedure using actual data from the CWS in order to determine the appropriate "reasonable price" to use if an actual price is found to be "excessive." To this end, we estimate separate conditional distributions for four broad commodity groups: petroleum products, farm products, coal, and chemical products. We then apply our competitive benchmark price approach to all potential "non-competitively" determined prices for several values of α less than or equal to 0.05. We then consider the total revenue implications of reseting any excessive prices to various "reasonable" price levels.

These competitive price conditional distributions could be estimated for more commodities and for narrower product groups (e.g., grain, hazardous materials) as long as there are sufficient observations to obtain credible estimates. Once this conditional distribution has been estimated for each commodity, the STB could use it to determine whether a shipper is being charged an "excessive price" for a movement or set of movements following the procedure described above given the shipment characteristics and a value of α. As we discuss below, the value of α could be different for different commodities depending on the location of the support of the distribution competitive prices versus the locational of the support of the distribution of "excessive" prices.

Estimating our conditional competitive price distribution relies primarily on data from the CWS. The dependent variable y_i is the natural logarithm of the average revenue per ton mile (ARTM) for the shipment deflated by the gross domestic product price deflator. This variable is the revenue received from a shipment divided by the product of the number of tons in the shipment and the distance traveled. Revenues are the sum of freight revenues (transportation-related revenues), miscellaneous charges, and fuel surcharges.[25] In the calculation for ton-miles, the variable "billed weight" was used for tons, and distance was calculated as the "total miles traveled for the shipment."

The elements of X_i, the vector of shipment characteristics are: (1) shipment distance (X_1), (2) shipment size (number of cars) (X_2), (3) the number of railroads involved in the movement (X_3), (4) the number of Class I railroads within 10 miles of the origin (X_4), (5) the number of Class I railroads with 10 miles of the destination (X_5), (6) a dummy to indicate whether the shipper owns the cars (X_6), and (7) a dummy to indicate that there is no water port within 50 miles of the origin (X_7), and (8) a dummy to indicate that there is no water port within 50 miles of the destination (X_8). Additional variables can be added to the vector of shipment characteristics, X. The elements of X selected for this implementation were based on two factors: (a) previous empirical research on the determinants of shipment rates and (b) the availability of the variables in the CWS and other publicly available data sets.[26] All of the continuous variables—distance, size, number of railroads—are measured in natural logarithms, to make their marginal distributions more symmetric. We experimented with different distances for constructing X_4, X_5, X_7, and X_8. Finally, fixed effects are included for the year of the movement, for the primary railroad in the movement, and for the five-digit Standard Transportation Commodity Code (STCC) categories. Each shipment in the CWS has an expansion factor, EF_i, that gives the STB's estimate of the number of shipments in the population of annual shipments with same observable characteristics as this shipment.

These conditioning variables are chosen based on availability in the CWS and past econometric studies that examine how rail rates relate to shipment characteristics such as distance, shipment size, and number of railroads involved in the shipment, as well as various measures of intramodal and intermodal competition (Boyer 1987; Barnekov and Kleit 1990; McFarland 1989; Burton 1993; Wilson 1994; Dennis 2000; Schmidt 2001; MacDonald 1987; MacDonald 1989; Grimm et al. 1992; Burton and Wilson 2006).[27]

To implement our nonparametric conditional distribution estimator, we first divide the vector X into two groups of variables: continuous (X_c) and binary (X_d) (this also include

[25]Fuel surcharges were introduced by railroads in 2003 but were reported in different CWS fields by different railroads. Some railroads included these surcharges in the freight revenue field and others included them in the miscellaneous revenue field. From 2009 forward, CWS has had a separate field for fuel surcharges. Therefore, our solution is to use total revenues, including these fuel surcharges, for the shipment as our shipment revenue variable.

[26]See, for example, MacDonald (1987 and 1989) and Wilson (1994).

[27] Shipment size is measured by carloads in the shipment. It is common practice for railroads to offer lower rates for multiple-car shipments.

categorical variables used for fixed effects). Using the dataset of observations classified as being competitive routes, we regress y and the columns of X_c on X_d and take the residuals, e_p and e_X. The each variable in e_X is then scaled by subtracting its mean and dividing by its standard deviation.

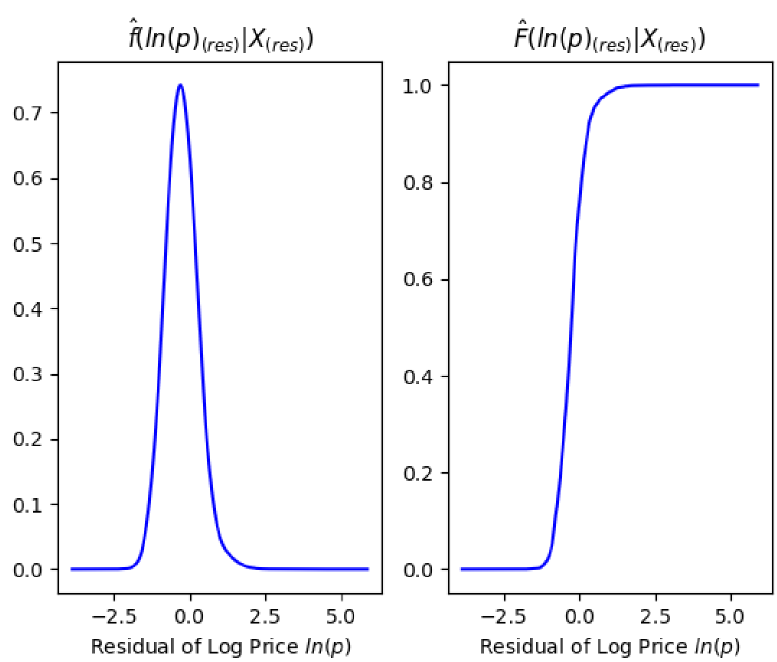
We then estimate the distribution $\hat{F}(e_p|e_X)$ using the process described above. Then, using the estimated coefficients from the regressions on the sample of competitive shipments, we compute e_p and e_X for the potentially non-competitive routes and then scale the variables in e_X using the mean and standard deviation from the competitive sample. We compute $\hat{F}(e_p|e_X)$ for these observations, and classify observations as non-competitive using α, as described above.

Results for estimating this conditional competitive price distribution model using petroleum products, farm products, coal, and chemical products data from the years 2000 to 2013 from the CWS are presented below.

Petroleum Products

There are 50,340 observations in the competitive dataset, and 36,073 in the potentially non-competitive dataset. The following figures display the estimated distributions $\hat{f}(e_p|e_X)$ and $\hat{F}(e_p|e_X)$, for a fixed value of X.

Figure 8: Conditional Density and Distribution for a fixed X



Tables 2 and 3 compute the percent of observations found to exceed the competitive benchmark price for that value of α in our test samples for petroleum products for each year from 2000 to 2013. The first column gives the year of the sample. The second column the sum of the expansion factors for all shipments that year and the third column is the sum of expansion factors for shipments that exceed the price benchmark in that year,[28] The final column is the ratio of the third column divided by the second column expressed as a percentage. The first line of each table gives the totals for each column for all of the years in the table. Across all years and for both $\alpha = .05$ and $\alpha = .01$ the frequency of excessive observations is less than or equal to 5 percent.

Table 2: Petroleum Products Estimated Population Classifications by Year, $\alpha = .05$

Year	Total Obs	# "Excessive"	% "Excessive"
	1376558	50970	3.703
2000	150276	3394	2.259
2001	120566	3952	3.278
2002	84216	4052	4.811
2003	82932	2856	3.444
2004	80452	3120	3.878
2005	94296	2952	3.131
2006	108212	5456	5.042
2007	102844	5076	4.936
2008	94992	3736	3.933
2009	88812	3700	4.166
2010	81804	3872	4.733
2011	87312	3328	3.812
2012	98588	2368	2.402
2013	101256	3108	3.069

In Table 4, we assess the impact of resetting shipment prices that are deemed to be excessive to different features of the conditional competitive price distribution on the revenues shippers earn from moving petroleum products over our sample period of 2000 to 2013. We consider three possible "reasonable" prices for shipments that have been deemed to be excessive using our benchmark price for given value of α. First, we re-set "excessive" prices to the conditional mean of the competitive price distribution. Second, we set it equal to the conditional median of the competitive price distribution. Last, we could set it equal to $PB(\alpha, X)$ the competitive benchmark price for that shipment. We show the percent in change total revenues over our sample period associated with replacing each "excessive" price with that "reasonable" price using the benchmark price $P(\alpha, X)$ for $\alpha = .1, .05, .01$.

Particularly, for the "reasonable" price set equal to our competitive benchmark price,

[28] The expansion factor for a shipment gives the estimated number of waybills in the population of shipments that the each waybill in the CWS sample represents.

Table 3: Petroleum Products Estimated Population Classifications by Year, $\alpha = .01$

Year	Total Obs	# "Excessive"	% "Excessive"
	1376558	12540	0.911
2000	150276	404	0.269
2001	120566	1092	0.906
2002	84216	1256	1.491
2003	82932	748	0.902
2004	80452	360	0.447
2005	94296	972	1.031
2006	108212	1264	1.168
2007	102844	1160	1.128
2008	94992	972	1.023
2009	88812	996	1.121
2010	81804	1104	1.350
2011	87312	836	0.957
2012	98588	732	0.742
2013	101256	644	0.636

the aggregate revenue implications for railroads of resetting the actual price to this price are less than 1.2 percent for α less than or equal to .05. Even for "reasonable" prices equal to the conditional mean and median, the revenue reductions are less than 3.1 percent for α less than or equal to .05.

To assess the extent to which shippers obtain rate relief by resetting the actual price to one of these three "reasonable" prices, we compute the average difference between the actual "excessive" price and the "reasonable" price for each of our measures of a "reasonable" price. Table 5 reports the average value of these price differences for the three "reasonable" price measures for values of $\alpha = .1, .05, .01$. The last line of the table reports that average value of actual prices for all of the prices in the test sample deemed to be "excessive" for that value of α.

These results demonstrate that even for the case of the "reasonable" price equal to our competitive benchmark, the average price change from the actual price to the "reasonable" price are a significant fraction of the average price that is deemed to be "excessive." For example, for the case of $\alpha = .05$, the average "excessive" price is \$ 18.38 and the average difference between the actual price and the "reasonable" price using our competitive benchmark price is \$ 5.25, which implies an average price reduction of more than 28 percent.

Table 4: Petroleum Products Percent Revenue Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
% change using mean p	-3.19	-2.20	-0.82
% change using median p	-5.61	-3.07	-0.97
% change using threshold p	-2.24	-1.13	-0.32

Table 5: Petroleum Products Average Dollar Price Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
\$ change using mean p	-10.03	-14.87	-24.97
\$ change using median p	-11.62	-16.44	-26.58
\$ change using threshold p	-4.01	-5.25	-7.51
Average p of noncompetitive obs	13.59	18.38	28.56

Farms Products

For Farm Products there are 53,205 observations in the competitive dataset, and 115,337 in the potentially non-competitive dataset. Tables 6 and 7 reproduce tables 2 and 3 for farm products. Across all years and for both $\alpha = .05$ and $\alpha = .01$ the frequency of excessive observations is less than or equal to 2.7 percent.

In Table 8, we show the percent change in total revenue for our sample period if we were to change prices that were classified as non-competitive to the three features of the conditional distribution of competitive prices described above. In this case, resetting "excessive" prices to any of our three 'reasonable" prices implies a less than 1.3 percent revenue reduction for α less than or equal to .05.

Table 9 reports the average value of these price differences for the three "reasonable" price measures for values of $\alpha = .1, .05, .01$. These results demonstrate that even for the case of the "reasonable" price equal to our competitive benchmark price, the average price changes from the actual price to the "reasonable" price are a significant fraction of the average price that is deemed to be "excessive." For example, for the case of $\alpha = .05$, the average "excessive" price is \$ 1.58 and the average difference between the actual price and the "reasonable" price using our competitive benchmark price is \$ 0.53, which implies an average price reduction of more than 34 percent.

Table 6: Farm Products Estimated Population Classifications by Year, $\alpha = .05$

Year	Total Obs	# "Excessive"	% "Excessive"
	1245895	27850	2.235
2000	107502	1667	1.551
2001	101372	2721	2.684
2002	100725	2316	2.299
2003	90607	1954	2.157
2004	85868	2152	2.506
2005	95520	2354	2.464
2006	98426	1938	1.969
2007	94673	1766	1.865
2008	87670	2404	2.742
2009	82393	2062	2.503
2010	81708	1493	1.827
2011	78675	1603	2.037
2012	74550	1654	2.219
2013	66206	1766	2.667

Table 7: Farm Products Estimated Population Classifications by Year, $\alpha = .01$

Year	Total Obs	# "Excessive"	% "Excessive"
	1245895	11963	0.960
2000	107502	743	0.691
2001	101372	1080	1.065
2002	100725	1050	1.042
2003	90607	654	0.722
2004	85868	588	0.685
2005	95520	1116	1.168
2006	98426	597	0.607
2007	94673	323	0.341
2008	87670	1153	1.315
2009	82393	1214	1.473
2010	81708	857	1.049
2011	78675	874	1.111
2012	74550	926	1.242
2013	66206	788	1.190

Table 8: Farm Products Percent Revenue Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
% change using mean p	-0.73	-0.83	-0.66
% change using median p	-1.88	-1.23	-0.73
% change using threshold p	-1.20	-0.80	-0.37

Table 9: Farm Products Average Dollar Price Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
$ change using mean p	-0.61	-1.02	-1.87
$ change using median p	-0.72	-1.13	-2.00
$ change using threshold p	-0.30	-0.53	-0.89
Average p of noncompetitive obs	1.06	1.50	2.43

Coal

For coal, there are 285,976 observations in the competitive dataset, and 158,068 in the potentially non-competitive dataset. Tables 10 and 11 break the classifications down by the year of the observation and use the CWS expansion factors to estimate population values for the number of "excessive" prices and frequency of "excessive" prices each year. For both $\alpha = .05$ the annual frequency of excessive observations is as high as 26 percent in 2006. With and $\alpha = .01$ the annual frequency of excessive observations never exceeds 9 percent.

Based on the results of the Monte Carlo study, coal is likely to be case of a product where there is significant overlap between the support of the distribution of competitive prices and the support of the distribution of non-competitive prices, which argues in favor of a value of α in the neighborhood of .01.

In Table 12, we show the percent change in revenue if we were to change prices that were classified as non-competitive for the three features of the conditional distribution of competitive prices. In this case, resetting "excessive" prices to any of our three 'reasonable" prices for the case of $\alpha = .05$ implies at least a 3.5 percent reduction in annual revenues. For the case of $\alpha = .01$, the largest percentage reduction in annual revenues is 3.4 percent, which provides a further evidence that $\alpha = .01$ is likely to be the appropriate choice of α for the coal.

Table 13 reports the average value of these price differences for the three "reasonable" price measures for values of $\alpha = .1, .05, .01$. These results provide additional evidence that there is significant overlap between the supports of the distributions of "excessive" prices and competitive prices. The average price changes from the actual price to a "reasonable" price set equal to our competitive benchmark price is 5 cents for $\alpha = .05$. The average "excessive" price for this scenario is 25 cents, which implies an average price reduction of 20 percent, which is a significantly lower percentage change than is the case for petroleum products or farm products.

Table 10: Coal Estimated Population Classifications by Year, $\alpha = .05$

Year	Total Obs	# "Excessive"	% "Excessive"
	1346433	123499	9.172
2000	313470	33024	10.535
2001	206174	8193	3.974
2002	211770	22563	10.654
2003	162456	6207	3.821
2004	153933	5724	3.719
2005	109765	7842	7.144
2006	35110	9217	26.252
2007	33924	7891	23.261
2008	33024	5599	16.954
2009	24077	4084	16.962
2010	20374	4413	21.660
2011	18557	4264	22.978
2012	12147	2794	23.002
2013	11652	1684	14.452

Table 11: Coal Estimated Population Classifications by Year, $\alpha = .01$

Year	Total Obs	# "Excessive"	% "Excessive"
	1346433	64086	4.760
2000	313470	25505	8.136
2001	206174	3048	1.478
2002	211770	12856	6.071
2003	162456	2770	1.705
2004	153933	2638	1.714
2005	109765	3410	3.107
2006	35110	3143	8.952
2007	33924	2881	8.493
2008	33024	1770	5.360
2009	24077	1515	6.292
2010	20374	1551	7.613
2011	18557	1237	6.666
2012	12147	956	7.870
2013	11652	806	6.917

Table 12: Coal Percent Revenue Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
% change using mean p	-4.42	-3.50	-2.16
% change using median p	-13.28	-9.31	-3.36
% change using threshold p	-6.09	-3.60	-0.97

Table 13: Coal Products Average Dollar Price Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
\$ change using mean p	-0.12	-0.12	-0.19
\$ change using median p	-0.16	-0.16	-0.25
\$ change using threshold p	-0.05	-0.05	-0.08
Average p of noncompetitive obs	0.25	0.25	0.37

Chemical Products

For Chemical Products there are 356,187 observations in the competitive dataset, and 197,624 in the potentially non-competitive dataset. Tables 14 and 15 break the classifications down by the year of the observation and use the CWS expansion factors to estimate population values of the number and the percent of excessive prices each year. For both $\alpha = .05$ the frequency of excessive observations is never higher than 6.8 percent, and is typically in the range of 3 to 4 percent. With $\alpha = .01$ the frequency of excessive observations never exceeds 1.2 percent.

Based on the results of the Monte Carlo study, chemical products is likely to be case of a product where there is less overlap between the support of the distribution of competitive prices and the support of the distribution of non-competitive prices than is the case for coal. This argues in favor of a value of α in the neighborhood of .05.

In Table 16, we show the percent change in revenue if we were to change prices that were classified as non-competitive for the three features of the conditional distribution of competitive prices. Resetting "excessive" prices to any of our three 'reasonable" prices for the case of $\alpha = .05$ implies at least a 3.2 percent reduction in annual revenues. For the case of $\alpha = .01$, the largest percentage reduction in annual revenues is less than one percent, which provides a further evidence that $\alpha = .05$ may be the appropriate choice for the chemicals.

Table 17 reports the average value of these price differences for the three "reasonable" price measures for values of $\alpha = .1, .05, .01$. These results provide additional evidence that there is less overlap between the supports of the distributions of "excessive" prices and competitive prices for chemicals than for coal. The average price changes from the actual price to a "reasonable" price set equal to our competitive benchmark price is \$3.31 for $\alpha = .05$. The average "excessive" price for this value of α is \$11.75, which implies an average price reduction of 30 percent, which is in the neighborhood of the values obtained for petroleum products and farm products.

In Table 16, we show the percent change in revenue if we were to change prices that were classified as non-competitive using the three features of conditional competitive price distribution.

Table 14: Chemical Products Estimated Population Classifications by Year, $\alpha = .05$

Year	Total Obs	# "Excessive"	% "Excessive"
	7477101	283347	3.790
2000	948045	36128	3.811
2001	750680	33533	4.467
2002	572671	38990	6.808
2003	542324	19950	3.679
2004	605448	15884	2.624
2005	635763	22872	3.598
2006	664846	20559	3.092
2007	501475	19857	3.960
2008	451544	12237	2.710
2009	407162	13286	3.263
2010	413085	13465	3.260
2011	395827	12610	3.186
2012	305394	12940	4.237
2013	282837	11036	3.902

Table 15: Chemical Products Estimated Population Classifications by Year, $\alpha = .01$

Year	Total Obs	# "Excessive"	% "Excessive"
	7477101	50791	0.679
2000	948045	4000	0.422
2001	750680	4890	0.651
2002	572671	6685	1.167
2003	542324	4152	0.766
2004	605448	2184	0.361
2005	635763	5600	0.881
2006	664846	3100	0.466
2007	501475	2424	0.483
2008	451544	2695	0.597
2009	407162	2819	0.692
2010	413085	3061	0.741
2011	395827	3330	0.841
2012	305394	3283	1.075
2013	282837	2568	0.908

Table 16: Chemical Percent Revenue Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
% change using mean p	-0.81	-1.53	-0.63
% change using median p	-5.62	-3.22	-0.81
% change using threshold p	-2.37	-1.19	-0.29

Table 17: Chemical Products Average Dollar Price Changes from Different "Reasonable" Prices

	$\alpha = .1$	$\alpha = .05$	$\alpha = .01$
$ change using mean p	-5.13	-8.27	-16.61
$ change using median p	-6.64	-9.81	-18.13
$ change using threshold p	-2.40	-3.31	-5.80
Average p of noncompetitive obs	8.55	11.75	20.04

A number of conclusions emerge from our Monte Carlo study and the application of our competitive benchmark price to data from the CWS. First, our Monte Carlo study finds that values of α less than 0.06 and greater than 0.01 appear to minimize the expected value of the square of misclassification errors for the types of conditional distributions of competitive prices and conditional distributions of "excessive" prices likely to be encountered in practice. Second, for these values of α, the vast majority of shipment prices in our test sample are correctly classified as competitive when they are truly competitive.[29] Third, for these values of α, even resetting the "excessive" price to the conditional mean or conditional median of the competitive price distribution is likely to have a relatively small adverse impact on the revenues earned by shippers for the four products considered. Fourth, resetting the value of an "excessive" price to the value of our competitive benchmark price has the smallest adverse impact on railroad revenues. Fourth, for all products we find that resetting "excessive" prices to any of our "reasonable" price produces economically meaningful price reductions for the effected shippers. For α less than .05, the smallest average percentage price reduction for mitigated shipments relative to the average actual "excessive" price is 20 percent.

Taken together, these results suggest that our benchmark pricing approach can be a low administrative cost approach for the STB to carry out its statutory mandate to protect shippers from excessive prices, while at the same time not adversely impacting the ability of the railroads to achieve the aggregate revenues necessary for their long-term financial viability.

[29]When the supports of the distribution of non-competitive prices and competitive prices overlap, most of the misclassification errors are due to classifying non-competitive prices as competitive prices.

V. Potential Use Benchmark Price Mechanism in Regulatory Process

There are a variety of ways to use the benchmark price mechanism to carry out the STB's mandate to protect captive shippers from ”excessive” prices. The competitive benchmark price approach could replace the R/VC ¡ 180 test for an ”excessive” price as the first step in the rate relief process. Alternatively, the benchmark price could supplement the R/VC ¡ 180 test to ensure that failure of this test is in fact due to a non-competitive price, rather than the methodological issues with the UCRS ”variable cost” (VC) measure discussed in Wilson and Wolak (2016).

Using the benchmark price approach to replace the R/VC ¡ 180 test for an ”excessive” price would end the STB's reliance on URCS ”variable cost” measures in making an ”excessive” price finding. This would likely require legislation to change this step in the ”excessive” price determination process. The need for legislative action raises the question who should set the value of α that determines the value of the benchmark price. Similar to the case of the R/VC ¡ 180 percent test, the value of α could be set in the legislation that implements the benchmark price. Alternatively, the law could provide legislative guidance to the STB in setting the value α. For example, the law could direct the STB to set α to minimize the sum of squared misclassification errors.

As is the case under the current rate relief process, a price that exceeds the benchmark level would not be subject to regulatory relief unless the STB also determines the rate charged is the result of a market dominance. The benchmark price mechanism can also provide useful input to this stage of the rate relief process. A railroad that sets a price that exceeds the benchmark level for its product and shipment characteristics could be required to identify the factors not included in X, the vector of observed product and shipment characteristics, that ”explains” this high price. Conversely, the shipper can argue that these factors do not ”explain” the high price charged.

This use of the benchmark price approach supports one of the recommendations for reform of the rate relief process from the NAS report, *Modernizing Freight Rail Regulation*, to use final offer arbitration to determine the ”reasonable” shipment price if the railroad is found to charge a price that exceeds the benchmark price and that price is found to be the result of a dominant railroad. The arbitrator could determine whether the factors proposed by the railroad ”explain” the higher price and therefore the shipper is not entitled to rate relief.

This arbitration process could provide input to the computation of future benchmark prices. If a certain factor not included in the vector of observed characteristics, X, used to compute the benchmark price is found by the arbitrator to ”explain” the higher price, the STB could require data on that factor to be compiled for all future shipments in the Waybill data. This factor could then be incorporated in the vector of observed characteristics, X.

For example, railroads argue that hazardous materials are more expensive to move and therefore charge higher prices to ship these materials. Based on the result of arbitration processes on this issue, the STB could require shippers to report shipment characteristics in their Waybill data that describe the dimensions of the hazardous materials in the shipment and these observable factors could be incorporated into the vector of product and shipment characteristics, X, used to compute the conditional distribution of competitive prices.

Even if no legislative change is made in the rate relief process, the benchmark price mechanism could be used in this process. It could provide as an additional check on whether a rate that violates the R/VC ¡ 180 percent test is in fact "excessive." It could also help focus the rate relief process on identifying the unobserved factor or factors that "explain" the higher price charged by the railroad. Finally, it could provide useful input to the STB in determining a "reasonable" price for the shipment in the event that the STB finds that a price is "excessive."

A final issue that the benchmark price approach can address is the impact of the selection of "reasonable" price on the annual revenue adequacy of the railroad. As shown in Section IV, setting the "reasonable" price using a percentile of the conditional distribution of competitive prices allows an analysis of the annual revenue implications different choices of α determining this reasonable price. Smaller values of α imply a larger value for the "reasonable" price and therefore a smaller reduction in annual revenues from resetting "excessive" prices.

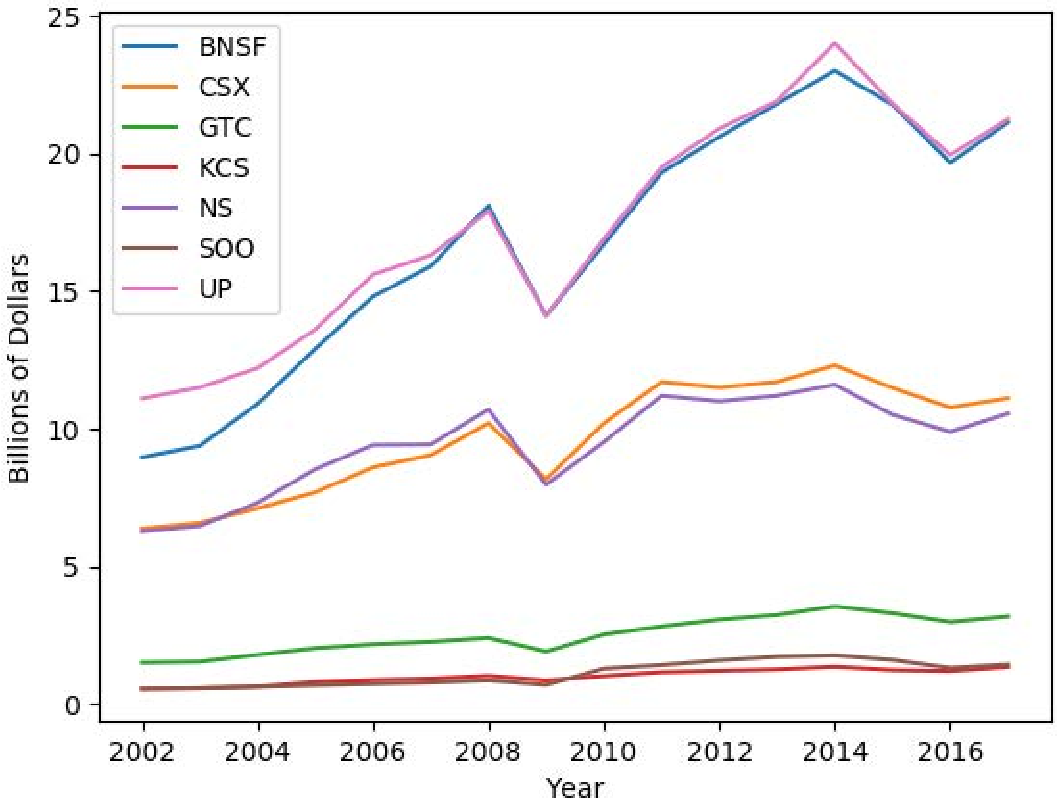
This logic suggests another factor to consider in setting the value of α: the year-to-year volatility in rail revenues from movements in involving the product under consideration. Figure 9 plots the annual operating revenues for the seven Class I railroads operating in the United States from 2002 to 2017.[30] The year-to-year variation revenues excluding the financial crisis period of 2009 to 2009 provides guidance for selecting the value of α. Based on these graphs, an annual revenue change of 5 percent is consistent with the year-to-year variation from trend growth in revenues over time for all of the Class I railroads.

This logic implies that those product categories that typically experience less year-to-year variation in revenues relative to trend should have lower values of α than those products that experience more year-to-year variation in revenues. Among our four categories of products, we would expect that coal typically experiences the least year-to-year variation in revenues, given that historically coal was used to produce baseload electricity. Petroleum, farm products and chemicals are likely to have higher year-to-year variation in product-level revenues

[30]BNSF: Burlington Northern and Santa Fe, CSX: CSX Transportation, GTC: Grand Trunk Corporation, KCS: Kansas City Southern Railway, NS: Norfolk Southern Corporation, SOO: SOO Line Corporation, and UP: Union Pacific

than coal. This logic implies that coal would have a smaller value of α than the other three products.

Figure 9: Annual Operating Revenues for Class I Railroads in the United States from 2002 to 2017



VI. Concluding Comments

The fact that a growing share of rail shipments are moving at rates that are determined under competitive conditions presents an opportunity to use this data to construct a conditional distribution of competitive prices given shipment characteristics that can be used to determine whether rate charged for shipment is "excessive." The computation of this benchmark price can be automatically updated each year given a sample of shipment prices and observable characteristics along with their expansion factors from the annual Carload Waybill Sample. Moreover, this conditional distribution of competitive prices can be updated to condition additional observable characteristics that are found to "explain" shipment prices.

This benchmark pricing approach can be used formally and informally in the rate relief process. Formal use would likely require a legislative change, but informal use could used to assess whether violation of the current standard for an "excessive" price is the result non-competitive conditions or the result of methodological issues with the existing approach to rate relief described in Wilson and Wolak (2016). The conditional distribution of competitive prices can also provide input to the process of determining a "reasonable" price, if the existing regulatory process finds that a price is "excessive" and the result of dominance.

Appendix A

This appendix describes our choice of the kernel function used to compute our estimate of $\hat{F}(y|X)$ and the procedure we use to estimate the vector of smoothing parameters a.

For $K(\cdot)$ we use the Epanechnikov kernel,

$$K(x) = \frac{3}{4}(1 - x^2) \ \textit{for} \ |x| < 1$$
$$= 0 \ \textit{otherwise}$$

and

$$K_a(X - X_i) = \prod_{j=1}^{J} \frac{1}{a_j} K\Big(\frac{X^j - X_i^j}{a_j}\Big)$$

where $a = (a_1, a_2, \ldots, a_J)$, and X^j is the j^{th} variable of X. Other choices of the kernel function $K(t)$ produced similar estimates of $F(t|X)$. Once the vector a is selected, our estimate of the $F(y|X)$ can be computed given a random sample of $(y_i, X_i')'$ and associated expansion factors EF_i $i = 1, 2, ..., N$. We choose values of a according to the bootstrap bandwidth selection approach analyzed by Bashtannyk and Hyndman (2001) and originally recommended by Hall et al. (1999).[31].

Our procedure for estimating the bandwidth parameter vector a for our kernel regression estimator of $F(y|X)$ first fits a rich polynomial regression

$$y_i = \beta_0 + \sum_{j=1}^{J} \beta_{j1} X_{ji} + \cdots + \beta_{jk} X_{ji}^k + \sigma\epsilon_i$$

where ϵ_i are regression errors that are assumed to be independent and identically distributed $N(0, \sigma^2)$ random variables and k is determined by Akaike's (1973) Information Criterion. The β's and σ are estimated from the data. We then form a parametric estimator $\tilde{F}(y|X)$ from this model based on the assumption that the ϵ_i are independent and identical normally distributed random variables. Then we simulate $l = 1, 2, ..., L$ bootstrap data sets $y^{(l)} = \{y_1^{(l)}, \ldots, y_n^{(l)}\}$ based on the observations $X = \{X_1, \ldots, X_n\}$ from this parametric model.

We then choose the vector a to minimize

[31] We also employed the cross-validation method set forth in Li and Racine (2008) to compute the bandwidth parameters. However, this method took an order of magnitude longer to run, due to the size of our data, without the resulting parameters being very far from the ones estimated using the method of Hall et

$$\tilde{M}(a; L, \mathbf{y}', \tilde{F}(\cdot|X)) = \frac{1}{L}\sum_{l=1}^{L} I(a; X, y^{(l)}, \mathbf{y}', \tilde{F}(\cdot|X))$$

where

$$I(a, X, y^{(l)}, \mathbf{y}', \tilde{F}(\cdot|X)) = \frac{\Delta}{N}\sum_{j=1}^{Y}\sum_{i=1}^{N}[\hat{F}(y'_j|X_i, a) - \tilde{F}(y'_j|X_i)]^2$$

where $\mathbf{y}'$ is a vector of Y evenly spaced values over the sample space of y, with $y_{j+1} - y_j = \Delta$. $\hat{F}(\cdot|X, a)$ is our non-parametric estimate of the conditional distribution of y given X and $\tilde{F}(y'_j|X_i)]$ the parametric estimate of this condition distribution.

Given a^*, the optimized value of a, we can compute $\hat{F}(y|X, a^*)$ for any values of y and X. The process of computing the "optimal" value of a described above can be automated, given a sample of $(y_i, X'_i)'$ for $i = 1, 2, ..., N$ as each step of the process has well-defined termination rule.

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