Investigating Cartel Behavior in the US Railroad Market 1880-1886

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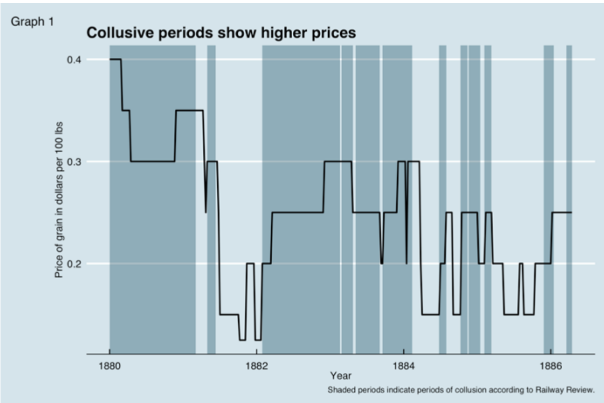
1. Summary statistics of the railroad market

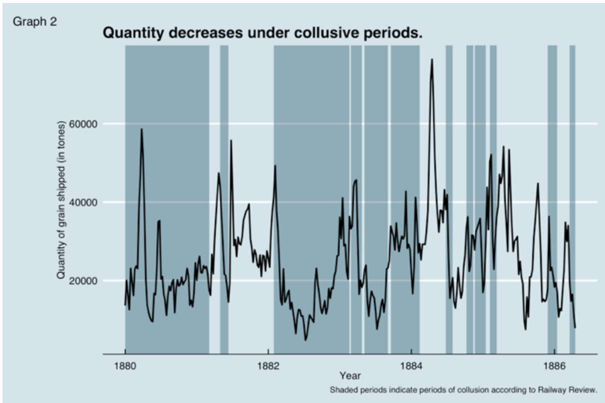
We begin with presenting summary statistics over the most important factors of the railroad markets. The majority of shipments consisted of grain, which is why this variable is a cornerstone of the analysis in this report. As shown in Table 1, the mean of the quantity of grain shipped per week was 25384.40 tons. The variability of shipments was rather large, however, as the standard deviation is 11632.77, with minimum being 4810.00 tons per week and the maximum being 76407.00 tons per week. Worth noting is also the grain rate (in dollars per 100 lbs). With a mean of 0.25 dollars, a standard deviation of 0.07 dollars and minimum/maximum of 0.12/0.40 dollars, we note that the price was rather stable over the period of study. Two other interesting variables are the ones capturing collusion: one from the perspective of the Railway Review and one derived from estimates. We note that the distribution of these differ: the mean of the former is 0.62 with a standard deviation of 0.49, while the later has a mean of 0.74 with a standard deviation of 0.44. Notably, there are 41 weeks where Porter estimates active collusion but Railway Review deems not, but there are no cases of the opposite.

Table 1: Descriptive statistics

Variable	Mean	S.D.	Min.	Max.
Quantity of grain shipped (tones)	25384.40	11632.77	4810.00	76407.00
Grain rate in dollars per 100 lbs	0.25	0.07	0.12	0.40
Collusion (Railway Review)	0.62	0.49	0.00	1.00
Collusion (estimate)	0.74	0.44	0.00	1.00
Great lakes open to navigation	0.57	0.50	0.00	1.00

Graphs 1 and 2 respectively plot the price of grain (in dollars per 100 lbs) and the quantity of grain shipped (in tons) over time, with shaded areas representing periods of collusion according to Railway Review. There appears over time to be a trend on average towards lower prices and higher quantities, although shipment quantity also displays a fair amount of noise. More interestingly, collusive periods appear to coincide with both higher prices and lower quantities shipped, relative to competitive periods. Both these observations are in line with theoretical expectations.





2. Factors facilitating and hindering collusion

Generally, cartels have to solve three main problems to survive: Entry, coordination and cheating. Industry-exogenous factors and the organizational structure of the cartel might enable overcoming these issues. In the JEC case, there are several such factors. The following characteristics of the railroad industry are likely to be especially important: *Low market concentration*: The railroad market was (and still is) characterized by low concentration and few players, making coordination easier. *High entry barriers*: It is expensive, time consuming and likely regulatory problematic to build new railroads. Hence the entry barriers are high. This makes the incentives for cooperation stronger, as the currently operating firms face a lower risk of having their market shares "stolen" by new (and potentially non-cooperative) entrant, compared to a market situation with low entry barriers (ceteris paribus). Note however that two entries occurred over the time period. According to Porter (1983), the cartel accepted these entrants. *Multi-market contacts*: The railroads partly covered different areas (from Chicago to different places along the Atlantic seaboard), allowing for distinct market share allotments to be used by the cartel: the easiest way for firms to collectively sustain and then split monopoly profits is to carve out respective regional monopolies. *Homogenous products:* The firms offer homogenous products, making it more clear on how to subdivide the market.

There are also several factors of the railroad industry that make collusion more difficult. We believe that the heavily unstable demand is the most important one as this makes cartel-internal coordination more difficult. This explains why "Information gathering and dissemination to member firms on weekly basis were the main functions of the cartel.".

3. Estimating supply and demand

Table 2: Demand and supply: OLS and 2SLS specifications using different collusion dummies

	Dependent variable:					
	log(tqg)	log(gr)		log(tqg)	log(gr)	
	OLS *Demand*	*OLS* *Supply*		*IV* *Demand*	*IV* *Supply*	
	(1)	(2)	(3)	(4)	(5)	(6)
log(gr)	−0.639***			−0.703***		
	(0.082)			(0.173)		
lakes	−0.448***			−0.441***		
	(0.120)			(0.121)		
log(tqg)		−0.126***	−0.094***		0.253	0.245
		(0.028)	(0.029)		(0.173)	(0.171)
po		0.273***			0.368***	
		(0.026)			(0.054)	
pn			0.290***			0.418***
			(0.029)			(0.072)
Grand Trunk entry		−0.200***	−0.229***		−0.202***	−0.229***
		(0.044)	(0.044)		(0.055)	(0.052)
New York Central addition		−0.172***	−0.180***		−0.173**	−0.182**
		(0.063)	(0.064)		(0.081)	(0.077)
Entry Chicago & Atlantic		−0.254***	−0.324***		−0.319***	−0.386***
		(0.046)	(0.045)		(0.065)	(0.062)
Exit Chicago & Atlantic		−0.467***	−0.432***		−0.208	−0.199
		(0.100)	(0.102)		(0.172)	(0.168)
Constant	9.176***	−0.096	−0.459	9.089***	−3.945**	−3.966**
	(0.135)	(0.285)	(0.306)	(0.247)	(1.758)	(1.770)
Observations	328	328	328	328	328	328
R^2	0.313	0.577	0.565	0.311	0.316	0.373
Adjusted R^2	0.282	0.552	0.540	0.281	0.276	0.336
1st stage F				22.9	13.1	13.4

Note: *p<0.1; **p<0.05; ***p<0.01
All specifications include monthly dummies.

We now turn to estimating the demand and supply functions, in accordance with their given definitions. We use PO as main measure of collusion, but also run a supply estimation using PN for completeness. The rest of this analysis focuses on the PO case. All of our regression specifications involve logarithms of all non-dummy variables.

Since both crop yields and customer demand for grain are bound to fluctuate seasonally, all of our regressions control for feature dummy variables for each month.

$$\text{Demand: } log(TQG_t) = \alpha_0 + \alpha_1 log(GR_t) + \alpha_2 Lakes_t + \Psi M_t + \varepsilon_t^d \ (1)$$

$$\text{Supply: } log(GR_t) = \beta_0 + \beta_1 log(TQG_t) + \beta_2 PO_t + \beta_3 S_t + \Phi M_t + \varepsilon_t^s \ (2)$$

PO is a dummy variable for whether collusion is active or not. We run regression (2) using both *PO* and then replacing it with *PN*. *M* is a vector of dummy variables for each month within the year. *S* is a vector of dummies corresponding to the five periods of market structure.

The result from the demand function estimation, which has logarithmized total quantity of grain shipped in tons (tgq) as dependent variable, is presented in column 1 of Table 2. The estimated coefficient for the logarithmized grain rate in dollars per 100 lbs (gr) takes the value of -0.639 and is statistically significant ($p < 0.01$). This means that the quantity demanded decreases as price increases, as expected, with a one percent rise in price implying a 0.639 percent decrease in quantity demanded. The estimated coefficient for the dummy describing whether the Great-Lakes were open to navigation takes the value of -0.448 and is also statistically significant ($p < 0.01$). This suggests that the quantity demanded decreased by 44.8 percent when the Great-Lakes were open to navigation. (We have included monthly dummies to control for seasonal variation in demand, which also correlates strongly with the availability of the Lakes route.)

The estimate of the supply function, which has logarithmized grain rate in dollars per 100 lbs (gr) as dependent variable, is presented in column 2 of Table 2. The estimated coefficient for logarithmized total quantity of grain shipped in tons (tgq) takes the value of -0.126 and is statistically significant ($p < 0.01$). Hence a one percent increase in total quantity shipped implies a 0.126 percent decrease of price. For the collusion variable (po), the estimated coefficient takes the value of 0.273 and is statistically significant ($p < 0.01$). As expected, periods where collusion holds are associated with higher prices, here 27 percent higher.

We also note that the estimated coefficients for the industries structural changes are negative and statistically significant ($p < 0.01$). The last event is merely a reversion of the penultimate event. Therefore, the coefficient was not expected to increase in magnitude, but rather to revert to previous levels. However, the temporal nature of these dummy variables means that they are liable to capture other time-related trends beyond changes in market structure alone.

4. IV estimation of supply and demand

In this part, we use an IV approach to estimate the supply and demand functions. Regression results are reported in Table 2, columns 4 and 5.

In order to estimate the demand function, we identified four entry events as supply shifters. If these events can be considered to only affect quantity through its effect on supply conditional on the monthly dummies and controlling for whether the Great Lakes were open for navigation, we can use them as instruments in a regression estimated using 2SLS. Treating the four events collectively, we think they are all relevant in the sense that they shift supply enough (by increasing the number of competitors, quantity increases in Cournot equilibrium) to qualify as relevant instruments. This is checked and confirmed for all the specifications in the *1st stage F* row of Table 2.

We find it hard to motivate that the instruments are valid. On the one hand, it is plausible that the demand for railway grain freight is independent of how many railway operators there are in the market. On the other, we noticed above that the events might capture time-variation that occurs simultaneously which we are not aware about, making it hard to argue why the time dummies (which they essentially are) fulfill the exclusion restriction. Additionally, the instruments may not be independent of demand or being "as good as randomly assigned" since the entries and exits might have occurred because of demand conditions. Ideally, we'd like to obtain shifts in the supply curve that occurred at random along the entirety of the demand curve in the way Angrist, Graddy and Imbens (2000) uses stormy weather as a supply shifter to estimate the average derivative of the demand curve for fish. But because of the constant elasticity of demand assumption, the assumption of random assignment is no longer crucial as the elasticity is the same along the entire curve. The estimated constant elasticity is inelastic, at -0.703 and significant meaning that a percentage increase in price decreases quantity demanded by 0.7 percent all else equal (with a caveat discussed under the headlines 6 and 7).

The supply equation was estimated using a demand shifter. In this case, we used the indicator for whether the Great Lakes were open to navigation as an instrument. This variable clearly shifts the demand for railway freighting since it indicates the availability of substitutes. Its relevance is also confirmed in Table 2 in the row *1st stage F*, where the F-statistic takes the value of 13.1. We also believe, conditional on the monthly dummies, that the variable fulfills both the exclusion restriction, and random assignment. Random assignment holds because the variable is driven by temporal weather conditions, which are exogenous once we control for the monthly dummies (we observe seven weeks within the year where the lakes' closure status varies between years). The exclusion restriction is plausible in the sense that more competition should not affect the price of freighting grain by train other than via its effect (through added competition which increases equilibrium quantity under the Cournot framework) on quantity freighted by train once we have accounted for seasonal effects. Note that since the Great Lakes variable proxies for weather, it might also shift the demand curve in later periods via its effect on harvest, although this channel is believed to be slight. Unfortunately, the relatively clean estimate of 0.253 is not significant at a conventional level given the standard error of 0.173.

The results of the regression are shown in columns 4 and 5 of Table 2. Using these estimates and the relationship that $\beta 2 = -log(1 + \theta/a1)$, we calculate the conduct parameter theta. It takes the value of 0.216. The estimated market conduct parameter is between 0 and 1, indicating that the average market conduct in the period is characterized by competition, but less competition than under perfect Bertrand competition.

We believe, like Porter, that competition occurs with quantity as the strategic variable. This means that if there were no collusion, the estimated conduct parameter estimates the parameter under the Cournot equilibrium outcome and tells us that the market is composed of the equivalent of 1/0.216 = 4.63 equally sized firms. Of course, there are periods of collusion according to the PO variable which makes the estimated value higher than that under a competitive Cournot equilibrium. This simply means that 4.63 equally sized firms is a lower bound of the number of equally sized firms present in the market.

5. A second estimate of the conduct parameter

We now rerun the IV regressions from *4. IV estimation of supply and demand*, with the change that we now use the estimated cheating variable PN instead of the reported PO in the supply equation. Regression results are presented in columns 4 and 6 in Table 2. Note that this variable does not enter the estimation of the demand function, which hence is the same as in the previous specification (column 4 of Table 2).

The estimate of the effect of the percentage change in price from a percentage change in quantity decreases to take the value 0.245 and is still insignificant at conventional levels.

Using the results in column 4 and 6 of Table 2 in the relationship: $\beta 2 = -log(1 + \theta / a1)$, we calculate the new conduct parameter theta. The parameter takes the slightly higher value of 0.240, indicating collusion to a higher extent than under the estimate of the railway review. This is consistent with what is described in Table 1, where *PN* is shown to have a higher average than *PO*, meaning that *PO* tend to be the more conservative measure of collusion.

6. Industry structure

The model deals with various changes in industry structure by dividing the study period into five subperiods, each representing different "eras" of industry structure. These periods are represented by four dummy variables (the first period is captured by the constant), taking the value of 1 during the era that the variable represent and 0 at all other times. In essence, the dummies are time dummies and will also capture other significant events that might have coincided.

For example, if our concern with these periods is motivated by a concern for industry structure specifically, and if we take industry structure to correspond exactly to the *set* of firms in the market/cartel, then there is no prima facie reason why the third period – from week 11 of 1883 until the Chicago & Atlantic's entry in week 26 of 1883 – should be distinguished from the fifth period, following C&A's departure in week 12 of 1886. Unless the market share allocations to the surviving cartel members following C&A's exit were different to the shares prior to their entry, Porter's model should constrain the coefficients on the period dummies to be equal to each other, or equivalently, to assign the same single dummy variable to both periods. If Porter wishes to capture other unobserved characteristics that vary, then he needs to motivate why these unobservables correspond to these periods in particular.

What's more, the question being posed ("*How much of the existence and success of the cartel relate to changes in industry structure?*") is whether a causal claim can be identified. Since the specifications in Table 2 don't address this particular causal claim per se using the proposed methodology, we have not tried to identify how much any change in industry structure explains collusion. One way to obtain an estimate with of this relationship, with minimal changes to the methodology, would be to look at the reduced form regression of the effect of the events on quantity demanded and the ensuing price and then use this information to estimate the effect on the likelihood of collusion. Another way would be to use logit regression to predict *PO* using the era dummies with appropriate controls.

Hence, the proposed methodology (i.e. the one Porter (1983) uses) suffers from serious constraints in this regard and cannot reliably answer the question of how much of the existence and success of the cartel that relate to changes in industry structure. A better approach should account for the concerns raised above.

7. Validity of model assumptions

The model used for the above made analysis relies on several assumptions, of which some are more restrictive than others. Here we discuss one assumption that is less restrictive and one that is more restricting for the current railroad cartel application.

One assumption that we find particularly restricting is the assumption that neither a time trend nor year dummies enter the structural equations for supply and demand. Time trends are generally better to control for than not and Graphs 1 and 2 hint at time trends over the six-year period. Altering the specification by adding a time trend (to the specification shown in column 4 of Table 2) renders the estimated demand curve entirely vertical: the estimated quantity elasticity of price is 0.012, with an associated p-value of 97%. With an already insignificant estimate of the supply curve gradient, we are unsure what to make of this analysis. Hence, we consider this assumption highly restrictive.

As for the opposite side of the spectrum, we believe that the assumption of homogenous goods is less restrictive. Assuming the railroad's customer is the farmer, and not the grain recipient, then the choice of railway firm is essentially a choice of destination city, between which the Law of One Price (the farmer's revenue for their grain) is generally observed. Costs are set by the railway operators which offer solutions with similar technology (there is no notion of a better delivery). Therefore, the prices of the railway operators should be similar and their customers will be indifferent, rendering the products undifferentiated. Hence, this is a less restrictive assumptions.

8. Generalization of the model

The dataset comes with two measures of collusion: *PO* (a reported measure) and *PN* (an estimated measure). Both *PO* and *PN* are imperfect measures of when actual collusion took place, i.e. they are both regressors suffering from attenuation bias. However, by using an IV approach, we can extend the model to cancel out this bias. By first assuming that the error component of the *PN* variable is independent of the true value of when collusion took place, and then assuming that *PO* is independent of the measurement error in the *PN* variable, we are able to obtain a consistent estimate of β_2 using *PO* as an instrument for *PN*. The basic idea is that *PO* predicts *PN* in the first stage of 2SLS and is only able to predict true variation in collusion, not the measurement error in *PN*.

We believe that both of the required assumptions are likely to hold. The first assumption is reasonable considering that the error in the variable follows mechanically from Porter's maximum likelihood estimation. The second assumption fails if both estimates fail to account for similar variation. This is deemed unlikely since the Railway Review and Porter have access to dissimilar information sets and are separated by a century.

With the above suggested IV approach, i.e. with *PN* in the structural equation, the implied market conduct parameter is 0.301 (calculated based on the results of the regression, not presented in this report). As a robustness check, we also run an IV estimation having *PO* in the structural equation. This changes the conduct parameter slightly, to 0.316. The first approach, with *PN* in the structural equation, is our preferred one, in accordance with the argumentation above.

The conduct parameter value of 0.301 from our preferred setup is higher than the values estimated without accounting for the measurement errors: these took the values 0.216 and 0.240 (see headlines *4. IV estimation of supply and demand* and *5. A second estimate of the conduct parameter)*. This difference is rather large, and hence failing to account for the measurement errors in the collusion variable leads to underestimation of the conduct parameter.