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Executive Committee
(1880 – 1886)**

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Geary WP2009/23
June 16, 2009

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Corn Market Dynamics and the Joint Executive Committee (1880-1886)*

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Abstract

Using principles of finance, we control for outside transportation rates and commodity market shocks, previously omitted variables, into Porter's (1883) analysis of industry demand, stability and pricing in the Joint Executive Committee Railroad Cartel. Our estimates of demand primitives are greatly enhanced by having cross-price effects. Finite periods of Cartel instability, as defined in the Aldrich Report (1893), are found to be triggered by unexpected commodity market shocks, and not by demand cycles, controlling for other factors. This is consistent with previous literature. We model pricing over marginal costs as a nonparametric function of a set of factors, including expectations of deterministic demand cycles and the expected probability of cartel stability. We estimate this nonparametric function, and linear marginal costs semiparametrically, as part of an equilibrium price path. Our estimated mark-up cycles during periods of stability, indicate that the JEC set rates over expected demand cycles as modeled in Haltiwanger and Harrington (1991).

KEYWORDS: DEMAND SHOCKS IN NEW YORK, DETERMINISTIC DEMAND CYCLES, ELEVATORS INVENTORY MANAGEMENT, JEC RAILROAD CARTEL, OUTSIDE TRANSPORTATION RATES, SPOT AND FUTURE WEEKLY COMMODITY PRICES IN CHICAGO AND NEW YORK, STRUCTURAL MODELING.

JEL classifiers: L92, L10.

*Andrew Coleman has kindly given us weekly transportation rate data for the Great Lakes and Canals as well as spot and future grain prices of the Chicago and New York Stock Markets. Without this we would not have been able to model the impact of outside transportation rates and commodity market shocks on the price and quantity movements in the Joint Executive Committee Railroad Cartel. This paper was presented at the IOS conference in Boston 2006 and 2009, CEPR/IIS productivity workshop in Dublin 2006 and EARIE 2006 in Amsterdam. We thank Silvi Berger, Robert Clark, Gregory Crawford, Peter Davis, John Haltiwanger, Joseph Harrington, Mike Harrison, Julie Mortimer, Ariel Pakes, Robert Porter, Paul Scott, John Sutton, Chad Syverson and Ciara Whelan for detailed comments.

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1 Introduction

The Joint Executive Committee Railroad Cartel (JEC) was in operation before the formation of the Interstate Commerce Commission (1887) and the passing of the Sherman Act (1890). The Committee operated explicitly as a legal Railroad Cartel during the period 1880 to 1886. A key issue for this paper, and most of the literature that worked on the JEC, is understanding how the Cartel sustained itself over deterministic cycles and in the presence of unexpected demand shocks, amongst other factors. To do this we incorporate previously omitted controls for expected outside transportation options and commodity market shocks into Porter’s (1983) “henceforth Porter” analysis of market demand, pricing and stability in the JEC Cartel.

Raw data from Coleman (2009) allow us to model the average weekly cost of moving grain (corn) between Chicago and New York. Coleman makes use of a theory based on the law of one price that allows for storage management and slow transportation over the Great Lakes (Lakes) to document how taking differences in the weekly spot price of corn in Chicago and the one month future in New York controls for the true expected shadow price of moving grain between the two cities. Lakes and Canals were the dominant mode of grain transportation between Chicago and New York, and Elevators played a key role in the demand for transportation. Elevators in New York did not accept high Winter transport costs, but rather used inventories to benefit from the low transportation costs in the open season. Transportation over the Lakes and Canals took three weeks and any shortfalls in New York (mainly for export), could be made up for, over Rail, in a few days. Even though the Lakes are closed for the Winter season, Coleman provides convincing empirical evidence that differences in the weekly price for corn in Chicago and New York stock markets mainly reflected the transportation costs of corn over the Lakes and Canals plus storage costs. Commodity prices in Chicago and New York stock markets, spots and futures, are independent of transportation prices and volumes set by the JEC cartel. Inventory management ensured the JEC potentially faced competition from the Lakes and Canals all year round. In this way inventory and pricing on the Lakes and Canals route imposed exogenous but, as we will document, predictable changes in demand on the JEC Railroad Cartel.

With simple extensions of the model in Porter, and with data on the expected rate of outside transportation options, we estimate improved demand primitives for the JEC, which are important to recover mark-ups from pricing. In addition, in terms of optimal price setting we illustrate how the JEC rate movements over marginal cost were driven by deterministic cycles, among other factors, to maintain Cartel stability. Hence, we also allow the mark-up to be driven by the expected rate of outside transportation options, amongst other factors.

This new data allows us to control for previously omitted data, but also to model and estimate demand, pricing and Cartel stability in an innovative way. Our modeling leads to rich estimates of weekly mark-up dynamics that were not previously estimated and documented for this Cartel. The price-cost margin from a generalized first order condition for pricing in an imperfectly competitive homogenous goods industry can be expressed as the following:

$$\frac{P_t - MC_t}{P_t} = -\frac{\theta_t}{\eta}. \quad (1)$$

Weekly price-cost margins can be expressed as the ratio of a *conduct parameter*, θ_t , and the total industry elasticity of demand η . We depart from the previous literature on the JEC in two important ways. First, we allow the JEC overall elasticity of demand, η , to be made up of two demand primitives, the own- and cross-price elasticity of demand. Demand will be found to depend on the expected price of

outside transportation options, among other things. Secondly, we model conduct, θ_t , as a nonparametric function of a set of observable variables.¹ Porter provides us with evidence that the JEC did experience finite periods of revisions to low mark-ups to sustain the Cartel, as modeled in Green and Porter (1984). We confirm that his estimates of such finite revision phases are very similar to the periods of Cartel instability, as defined in the Aldrich Report (1893).

We also model the causes of Cartel instability. Following Ellison (1994) we face-off deterministic cycles against unanticipated demand shocks as triggers of finite periods of instability, amongst other factors. Consistent with Ellison, we find that errors in such expectations, driven by unexpected commodity price shocks, are the key reason for the JEC spinning into finite periods of instability.² One important component of our modeling of θ_t , will be the expected probability of the Cartel in the next period being stable or not, amongst other controls. We work with precisely the same functional form for cost employed by Porter, but similar to Appelbaum (1982) we model Porter’s hidden regime (the conduct parameter) with a set of observables entering a nonparametric function. We wish to show how the inclusion of previously omitted data into this nonparametric function leads to richer mark-up dynamics, particularly when the Cartel is stable.³ We include the following observables into a nonparametric modeling of what was Porter’s unobservable (the mark-up): expected price of outside transportation options; estimated expected probability of Cartel stability; and movements in the internal incentive compatibility constraint (ICC) generated by anticipated demand cycles and not captured by the outside transportation options - as motivated by Haltiwanger and Harrington (1991). We capture the latter with a strictly exogenous count on the number of weeks that the Lakes are open and on the number of weeks to Lakes opening. We use these variables to proxy for expectations of increasing (decreasing) demand as we move along the weeks in the Lakes open (closed) season. Our modeling of pricing is conditioned on the probability of being in a stable regime in the next period and is estimated simultaneously with demand.

Overall we document a much richer and more general model of the factors driving JEC pricing above marginal cost (mark-up). Taking this mark-up with demand primitives we test for important properties in the dynamics of price-cost margins for this Cartel and find support for cyclical pricing as uncovered in Haltiwanger and Harrington (1991). To test the Haltiwanger and Harrington (1991) theory during the collusive periods, we regress price-cost margins during upswings and price-cost margins during downturns on a quartic function of the demand business cycle. The Haltiwanger and Harrington (1991) theory seems to be validated: for the same level of demand, the price (mark-up) is lower when the JEC is in a period of prolonged decline in demand, compared with that coming into a period of prolonged increases

¹Theory based on repeated games suggests that the Bresnahan’s (1989) θ is not static, as the intensity of price competition (market share rivalry) can vary over time. The way one models demand impacts the trade-off between one shot gains and discounted losses in incentive compatibility constraints in repeated games. This has been shown to generate very different time paths of the conduct and equilibrium price-cost margin (see for example Green and Porter (1984), Rotemberg and Saloner (1986), Haltiwanger and Harrington (1991) and Fabra (2006)). Genesove and Mullin (1998) provides us with a nice overview of the empirical issues surrounding the estimation of the generalized first order condition for pricing in homogenous good industries.

²Several theoretical papers have discussed this problem within the JEC, both from traditional, and game theoretic frameworks. The focus of this work has been on the apparent causes of “price wars” identified by Porter (1983), Ulen (1983), Porter (1985), Ellison (1994), Rotemberg and Saloner (1986), and Vasconcelos (2004). The core aim of the Ellison paper is to try and understand plausible trigger strategies that could send the Cartel into finite periods of punishment. His main finding is that unexpected demand shocks in the AR(1) residual of demand triggered the price war. This is tested against a Rotemberg and Saloner (1986) effect where the ICC comes under pressure when anticipated demand is high but low in the next period. Using data on commodity markets in New York, we intend to show that unanticipated commodity market shocks in New York were the trigger and not the cyclical nature of pricing as controlled by us. This is compatible with the findings of Ellison. As in Ellison, unusual movements in the market share of companies are not found to be the culprit. It seems that a common external unanticipated commodity shock was the trigger, consistent with the mechanisms in the trigger strategy discussed in the Green and Porter (1984) paper.

³We provide a direct comparison of our results with Porter, and for this reason make no attempt to separate out this function in pricing from costs using the techniques suggested in Berry, Levinsohn and Pakes (1995).

in demand. We see the important role of expected demand on mark-up cycles, reiterating the findings in Borenstein and Shepard (1996).

To sum up, the Porter study is regarded by most as a classic IO paper and the best analysis of a functioning cartel with imperfect observation. Incorporating previously omitted variables, using principles of finance, into an analysis of demand, pricing setting and stability in the JEC Railroad Cartel, does give us important new insights into rate setting in the JEC. While the results are broadly similar to Ellison (1994) in terms of our modeling of stability and demand, we find that the anticipated cyclical nature of demand is important for mark-ups (pricing) during periods of Cartel stability. Incorporating previously omitted variables in our modeling of mark-ups dynamics allows us to use an innovative semiparametric approach to estimating a generalized first order condition for pricing in an imperfectly competitive homogenous good industry. The resulting mark-up dynamics are very rich. In terms of lessons for today, the paper suggests that illegal price co-ordination can be detected in markets where firms must price over deterministic demand cycles.

In section two, we describe the data and literature. In section three, we replicate Porter and introduce our extension. In section four we provide results. Finally, we draw some conclusions.

2 The Data and Literature

The JEC managed East-bound freight shipments of grain, flour and provisions from Chicago to the Atlantic Coast. Grain was by far the most important commodity for the Cartel. The JEC set official rates and market share allotments, and managed clearing arrangements for those above and below their allocated tonnage for traffic out of Chicago. All members of the Cartel had full information on official rates, tonnage of traffic by each company and any deviation between allocated and actual tonnage. These statistics were published in weekly reports in the *Railway Review* and the *Chicago Tribune*. Porter employs a time series Cartel level data set, previously collated by Ulen (1979), to provide evidence of revisions to a low mark-up by the Cartel for finite periods. This finding is consistent with how to keep a cartel sustainable in the optimal equilibrium model of Green and Porter (1984). The top part of Table 1 provides summary statistics for the variables that he utilized. The period of reference spans from January 1, 1880 to April 18, 1886, for a total of 328 weeks.

Ellison (1994) provides us with another important empirical paper on the JEC. Building on Porter he imposes a Markov structure on the transitions to finite periods of low pricing to allow him model the causes of “price wars”. He estimates the parameters of the demand and pricing model of Porter by maximizing the joint likelihood of a system of demand, pricing and paths of transitions into and out of the Cartel instability. In addition, he imposes an AR(1) structure in the residuals of the Porter demand function and finds evidence of hidden regimes (omitted variables) in demand. We address this issue by bringing some key omitted variables into the demand function, most importantly the expected outside transportation rate. The core aim of the Ellison paper was to try and understand plausible trigger strategies that could send the Cartel into finite periods of punishment. He tested, but found little evidence of, four triggers constructed from the firm (railroad) level data, each designated to proxy for signals of cheating by firms inside the Cartel. Computing these variables requires having firm-level data on assigned quotas and actual market shares. We replicate his variables for use in our empirical model of Cartel stability. We document our reproduction in Table 1. The first of Ellison’s variables, BIG1, is aimed at capturing a particularly high market share for one of the firms in the cartel and is computed as:

$\max_i \frac{(s_{it} - \bar{s}_{it})}{\sigma_i}$. The market share of firm i is defined as $s_{it} \equiv \left(\log Q_{it} - \frac{1}{N_t} \sum_j \log Q_{jt} \right)$, with \bar{s}_{it} denoting the average market share over the previous twelve weeks.⁴ The heteroscedastic parameter σ_i indicates each firm’s standard deviation. N_t denotes the number of firms in the Cartel in period t . BIG2 is a variant of BIG1, with the only difference being that $s_{it} \equiv \frac{Q_{it}}{Q_t}$. BIGQ is also a variant of BIG1, which uses s_{it} as defined in BIG1, but computes \bar{s}_{it} over the allotted market share a_{it} . The last of the Ellison’s variables is SMALL1. Its role is to detect an unusually small market share for one of the firms in the Cartel. It is calculated as the absolute value of the $\min_i \frac{(s_{it} - \bar{s}_{it})}{\sigma_i}$, conditional on having $\min_i \frac{(s_{it} - \bar{s}_{it})}{\sigma_i} < 0$ (zero otherwise), where s_{it} and \bar{s}_{it} are those earlier defined in BIG1.⁵ As in Ellison, unusual movements in the market share of companies are not found to be the trigger. It seems that a common external unanticipated commodity shock is the culprit.

A final focus of Ellison was on the cyclical nature of pricing in the JEC. He finds little evidence that the cyclical or seasonal nature of demand had any impact on the general run of pricing or on a transition to “price wars”.

We construct variables from grain commodity markets that will control for external pressures to the JEC coming from outside transportation options and commodity market shocks in New York. Coleman (2009) had some key insights into the functioning of the late-nineteenth century transportation of grain between Chicago and New York. To facilitate the export of grain from the Great Plains to Europe after harvesting, there was a major rush to get grain over the Great Lakes and Canals to New York for storage in Elevators. The slowest and least expensive method was to travel to Buffalo by ship via the Great Lakes, and then on to New York along the Erie Canal (purposely enlarged during the period 1836 and 1862). This took approximately three weeks. A faster and more expensive method, taking ten days, was to ship it to Buffalo and then use rail on New York. This was useful particularly as the Canals would freeze up before the ports of the Lakes. Transportation over the Great Lakes was not available between November and late April however, as both the Canals and the ports of the Great Lakes were frozen. The fastest and most expensive method, available all year round, was to send grain over three days by rail to New York. The rail route could be used to top-up any shortfalls all year round. Generally, the market tried to stock inventories using the cheap and slow (closed in winter) mode of transportation. During the period 1878 and 1890, Coleman estimates that 95 per cent of corn that was transported in the open water season was shipped by Lakes. From the Aldrich Report (1893) we have various alternative measures of Lakes open/closed compared to Porter. Table 2 documents the number of weeks that Porter’s Lakes (L), and our Lakes and Railroads (LR) and Lakes and Canals (LC) remain open, for each year comprising the 328 weeks period.⁶ Canals freeze before the ports of the Lakes, and hence we see longer periods of Lakes open in the case of Lakes and Railroads. The duration of Lakes open using L , LC and LR dummies are very similar, and for that reason in the rest of the analysis we stay loyal to Porter and employ his Lakes dummy, L . Table 2 also describes the trend of periods of stability, measured by PO and PR . PO is a variable that Ulen (1978) constructed on the basis of internal reports of “price wars” within the Cartel (the variable is included in the list of Porter’s variables displayed in Table 1). As in Porter we are not fully confident in that variable, and so we propose another binary variable for periods of collusion denoted by PR . Our PR variable is set to one when the JEC grain rate was equal to the Chicago-New York grain rate from the Aldrich Report that Railroads, including the JEC, tried to peg to. From the table it emerges that PO and PR are similar, but the number of disruptions to Cartel

⁴For the first twelve weeks we average over any previous available week.

⁵In our data two observations have $\min_i \frac{(s_{it} - \bar{s}_{it})}{\sigma_i} > 0$, and thus have SMALL1 equal to zero.

⁶We utilize prices for shipments over Lakes and Railroads, and Lakes and Canals to recover the number of weeks that Lakes and Railroads, and Lakes and Canals, are open.

pricing in the JEC is not as great using the PR dummy. It turns out to be very similar to the PN cheating binary variable estimated by Porter in his hidden regime model, as confirmed by the mean values and standard deviations reported in Table 1. Our use of data on PR turns out to be important in our empirical methodology. We will estimate demand and pricing simultaneously but condition the pricing equation on the expected probability of cartel instability. Our variable PR will be modeled as a ARMA(1,1) linear probability model.

Coleman shows that generally speaking the weekly discrepancy between a future commodity price in New York and a spot commodity price in Chicago can be considered a good proxy for the expected average transportation and storage costs of moving grain from Chicago to New York. This assertion is empirically backed up using actual data on transportation rates and storage costs from the Aldrich Report. In general the presence of inventories allowed most of the shipments of grain to benefit from the slow and cheap option of transportation over the Lakes and Canals all year round. Table 1 presents definitions and summary statistics for a list of variables we constructed from his raw data. We define the log of the expected outside option in transportation rates facing the JEC as the following:⁷

$$gr_t^{*E} = \ln \{ E_t [Z_{t+1}^{NY}] - Z_t^C \}. \quad (2)$$

It is a maintained assumption that price setting on the Lakes and Canals route and inventory management could not be influenced by the Railroad Cartel, but pricing on the Lakes and inventory management could impose exogenous demand cycles on the Railroad Cartel. The speed of the delivery by the JEC Cartel ensured that if any weekly top ups were necessary in New York to meet demand, the Railroad Cartel would oblige. The +1 in the expectation of Eq. (2) postulates that it takes one period to ship the grain via the Lakes from Chicago to New York.

The actual rates for alternative modes of transportation are available from the Aldrich Report. This can be compared to the expected transportation rate that uses the New York future (delivery within one month) net of the Chicago spot price, (GR^{*E}). Figure 1 (a) to (i) depicts the pattern of weekly shipment rates between Chicago and New York in each year, including the JEC rates (Porter's GR), the Great Lakes and Canals rates ($GRLC$), and GR^{*E} . We take the latter to represent the true expected outside transportation options for the JEC when setting its rate. We notice that GR^{*E} shares the same trends of the JEC rate, GR , and the rate for shipments over the Lakes and Canals, $GRLC$. Its level is closer to, but higher than, the Great Lakes and Canal rates as it includes storage costs and the need to use Railroads. We note that the rate rises at the end of the Lakes open period, a trend that benefits both Railroads and the Steamship companies that operate over the Lakes and Canals. Our expected outside transportation rate variable highlights the role that inventories (controlled by the Elevators) had in smoothing rate fluctuations over the Lakes open and closed seasons. New York did not accept high Winter transportation costs, but used inventories to benefit from the low transportation costs of the Great Lakes and Canals in the open season. The figures seem to validate our choice of GR^{*E} as a proxy for the rate of the expected outside transportation mode. Table 3 further confirms our choice of variable, by showing a strong positive correlation between GR^{*E} and the rates of alternative modes of conveyance.

It is interesting to explore whether our expected outside transportation rate, GR^{*E} , has a determin-

⁷Indeed if we had to remove our assumption of prompt delivery for Railroads and one period delivery for Lakes, the difference between Chicago and New York would proxy for general transportation costs, i.e. it would also be inclusive of the rates charged by the JEC Railroad Cartel. Yet, this should not be worrisome, since Coleman unveils that the JEC had a rather marginal role in the total amount of grain carried to New York via Chicago. Our proxy is also valid when the Great Lakes are frozen, since competition from non-JEC Railroad Cartel was present as were inventories from the Great Lakes in New York.

istic business cycle. We first look at the rates before the Cartel years (1878-79) in Figures 1(a) and (b). During Lakes closed the rate increased and then decreased. Such downward revisions on Railroads rates in the weeks before Lakes opening could reflect expectations of the Lakes open regime. During Lakes open the rate decreased up to harvesting then increased as we moved to the closing of the Lakes. The pressure on the price came from New York trying to build up inventories for the Winter after the harvest came in. These movements in the expected average transportation rates before the formation of the JEC suggest to us that the opening and closing of the Lakes had effects on pricing in the weeks running up to Lakes closing and opening. In addition to controlling for exogenous anticipated movements in the price of outside transportation options to the JEC, whose movement should influence current demand and pricing (via the ICC inside the cartel), we also control for anticipated exogenous demand cycles - as motivated by Haltiwanger and Harrington (1991). This is done by creating two variables that reflect the cumulated number of weeks that Lakes have remained open at a given point in time in a year, NWO , and the countdown on number of weeks until the Lakes re-open at a given point in time in a year, NWC . NWO starts with a value of one associated with the first week the Lakes are accessible to navigation, and reaches its maximum the week prior to Lakes freezing again. The variable is set to zero during Lakes closed for navigation. As for NWC , it has its maximum the first week the Lakes are not accessible to navigation and reduces to a value of one the week before the Lakes reopen to navigation. The variable is set to zero during Lakes open. Rather than having a simple Lakes open and closed dummy we have varying degrees of pressures coming from the expectations of Lakes opening and closing represented by NWC and NWO which exhibit an asymmetric sawtooth profile. The latter represents the pressure to transport grain to inventories in New York after the harvest to avoid exposure to high transportation prices during the Winter. The former represents Elevator's increased ability to bargain with the JEC as the weeks to Lakes opening come nearer. We use these variables to proxy for expectations of increasing (decreasing) demand as we move along the weeks in the Lakes open (closed) season. Could they just reflect week effects in current demand rather than expectations of demand? Maybe, but we will verify, post-regression, that for the same level of current demand, in either Lakes open or closed, estimated mark-ups are higher going into a period of growing demand and lower going into a slump.

During (1880-1886) these trends in high and low expected outside transportation rates in both Lakes closed and open periods outlined above are present, but not in all years. In order to plot our expected outside transportation rates to a JEC business cycle, we first create a variable that avails of the Hodrick and Prescott (1997) filter and estimate the demand business cycles, \widehat{BCQ} . We plot the smoothed cycles against the actual demand in Figure 2. We note that the smoothed cycles indicate that demand for the JEC was not always higher in Lakes closed periods of each cycle. One might have assumed that the JEC did more business in the Winter when competition was weak, but inventory management in New York clearly made demand cycles for the JEC over Lakes open and closed regime more complex, allowing competition from the Lakes and Canals to have an all year round effect. In four out of the six Lakes open periods we see shipments increasing as the number of weeks to Lakes closing comes closer (when prices tended to rise). In most of the Lakes closed periods we see output increasing as the number of weeks to Lakes open shorten (when price tended to fall). The weeks that did not have such cycles tended to be when our PR dummy indicated a period of cartel instability. For this reason we plot the smoothed output cycle against our expected outside transportation rate, GR^{*E} , along with NWC and NWO , in Figure 3.

Overall we feel that we can control for exogenous deterministic cycles that should have an influence on JEC demand and pricing during periods of Cartel stability. We will also examine their role in terms of Cartel instability, while allowing for an unexpected break in the cycle to play a role here. We do this by

controlling for unexpected commodity market price movements. Unexpected commodity market shocks have the ability to change expected demand by Elevators and create a mistake in the calculation of an expected transportation rate for moving grain between Chicago and New York. We explore whether such external shocks lead to errors in JEC rate setting which in turn might trigger a period of Cartel instability.

Elevators determine the optimal demand for transportation based on future commodity prices and inventory models. Their plan was simple: when the harvest came in there was pressure to build inventories using the cheaper Lakes transportation during the latter half of the Lakes open period. The inventories could be used even when the Lakes were closed. Anytime inventories fell below a certain threshold, Elevators urged to top them up as soon as possible. Elevators had the key role of storing the commodity and providing a hedge against random consumption and harvest shocks. Based on the information they had available, they solved inter-temporal (dynamic) models to determine the optimal amount of grain to keep in stock. A by-product of their optimization was the demand for transportation.

We relate the amount of grain available as inventory in Elevators as follows:

$$Y_t = Y_{t-1} + M_t - C_t, \quad (3)$$

where M_t is the amount of grain imported in period t (mainly from Chicago) and C_t is period t consumption (mainly the amount of grain shipped to Europe). The volume imported is the result of transportation by ship and/or train.⁸ Similarly to Thurman (1988) and Pindyck (1994) we formulate the cost of holding inventories as the sum of a unit cost for the physical use of Elevators, u , and a function of current inventories, future expected consumption, and current commodity prices, $F(Y_t, E_t[C_{t+T}], Z_t)$. We assume F to be a well behaved function, convex in Y and increasing in C and Z . The negative of the marginal cost of inventories is the net benefit of an extra-unit of inventory, and is known in the literature as “marginal net convenience yield”,⁹

$$MNCY(Y; u) \equiv -F_Y - u, \quad (4)$$

where the partial derivative of F with respect to the argument Y is assumed negative, $F_Y < 0$, and the cross derivatives F_{YC} and F_{YZ} are assumed to be zero, $F_{YC} = F_{YZ} = 0$. We sketch the marginal net convenience yield function in Figure 4.

The presence of future contracts and the no arbitrage condition, due to all profitable opportunities being exploited by an optimal allocation of inventories across time, require the following equality condition to hold

$$MNCY(Y_t^E) = Z_t - \left(\frac{1 - \delta}{1 + r} \right)^T E_t [Z_{t+T}]. \quad (5)$$

That is, the difference between a spot commodity price Z_t , and the future commodity price T periods ahead, Z_{t+T} , discounted for the depreciation commodity rate (δ) and forgone interest rate (r), can be used to identify the marginal net convenience yield. As documented in Coleman, New York (NY) was by far the main receiving city from Chicago (C). So, we can use the difference between a spot and a future price in New York as a good measure of the (expected) marginal net convenience yield. This will be a good control for expected demand in New York as perceived by the JEC and its competitors. Without

⁸Given that Railroads can convey grain within three days, we assume that they are able to provide immediate delivery (within the week). In addition, we postulate that the alternative modes of transportation meet deliveries within the following period. In this way M_t casts the sum of transport by Railroads (R) and by Lakes (L) as $M_t = M_t^R + M_{t-1}^L$.

⁹A term introduced by Working (1949).

loss of generality, in the rest of the paper we utilize a simplified version of Eq. (5) that assumes $\delta = r = 0$.

$$MNCY_t^E \equiv MNCY(Y_t^E) = Z_t^{NY} - E_t [Z_{t+1}^{NY}]. \quad (6)$$

Our next variable captures errors in the expectations of commodity prices in New York. This will be a key variable in our modeling of Cartel instability. Our error in expectations variable is defined as,

$$ER_t = E_{t-1} [Z_t^{NY}] - Z_t^{NY}. \quad (7)$$

If Eq. (7) turns out to be negative, the realization of the commodity price in New York at time t , i.e. a spot price at time t in New York, would turn out to be higher than that expected at time $t - 1$. Note that the expected future price in New York enters both the marginal net convenience yield and our proxy for the expected transportation costs. A negative error in expectations at time t goes along with the two inequalities at time $t - 1$: $MNCY_{t-1}^E > MNCY_{t-1}$ and $gr_{t-1}^{*E} < gr_{t-1}^*$. The former suggests that the Elevators have accumulated a level of inventories below the optimal level that they would have built up under certainty. The Cartel realizes that it has underestimated demand in its price and quantity setting. The inequality of gr^* suggests that the Cartel expected the price of its competitors to be lower than it would have been framed under certainty. We will empirically estimate the impact of gr^{*E} and $MNCY^E$ on the general run of demand and price setting in the JEC. We would expect the rate of the outside transportation options to the JEC to come in positive in our model of demand and optimal price setting. An error in the expectation of the price of the outside option as outlined above would create a situation that the JEC should have set a higher rate and transported more shipments. This represents a clear loss in revenue for the Cartel. We will examine whether errors in expectations in prices of New York commodity markets are factors, among others, that push a higher probability of instability in the JEC. The analysis above summarizes the data previously used and motivates the use of the new data that we use to extend the basic structural model in Porter to be outlined in the next section.

3 The model

In this section we first delineate the model developed by Porter. We then introduce our approach to modeling and estimation. Like Ellison (1994), our extensions are done to tackle the issue of omitted variables in demand, to explore the causes of Cartel breakdown and to evaluate the impact of deterministic demand cycles on pricing, shipments and stability. Unlike Ellison we use a two-step semiparametric procedure which is largely motivated by our use of previously omitted data into the system of the model. More data allows us to have less structure in the estimation of stability, mark-ups (pricing) and demand. While the results are broadly similar to Ellison in terms of our modeling of stability and demand, we do find that the anticipated cyclical nature of demand is important for mark-ups (pricing) during periods of Cartel stability. Before we outline the model and our extension, we bring attention to the particular notation that we make use of. From here forward, lower case letters will denote natural logs of their original variables (i.e., gr will stand for $\ln GR$).

3.1 Porter

Demand Equation

$$q_t = \alpha_{0[t]} + \alpha_1 gr_t + \alpha_3 L_t + U_{1t}, \quad (8)$$

where gr_t is the natural log of the JEC grain rate per bushel shipped in week t , and q_t the natural log of the total quantity of grain shipped by Railroad that week. L_t is a dummy equal to one when the Great Lakes are open to shipping, and zero otherwise. U_{1t} is a mean zero error term. The parameter α_1 is expected to be negative. The parameter α_2 is purposely omitted and will be introduced in the next section, but we can anticipate it is going to be the parameter associated with the expected outside transportation grain rate. The time-varying coefficient $\alpha_{0[t]}$ encompasses a constant and month dummies.

Pricing Equation

Porter estimates the following pricing equation:

$$gr_t = \beta_{0[t]} + \beta_1 q_t + \beta_2 S_t + \beta_3 I_t + U_{2t}, \quad (9)$$

where U_{2t} is a mean zero error term generated by errors in marginal costs. This error term and the first part of the pricing equation, $\beta_{0[t]} + \beta_1 q_t + \beta_2 S_t$, are assumed to be the linear marginal cost function. He denotes with S_t a set of structural dummies that accommodate entry/exit and with $\beta_{0[t]}$ a constant augmented with month dummies. The remaining variable, I_t , is a dummy that equals one during a collusive regime, and zero otherwise. This is motivated by Green and Porter (1984) to capture a time varying conduct parameter θ_t . The key assumption is that there are only two regimes: one that is collusive and one that is reversionary. We will model conduct using a nonparametric function of several observable variables to capture interesting week to week dynamics in θ_t . This is a key departure from Porter and Ellison in our modeling of mark-ups. Ellison, when he interacts I_t with indices of anticipated cycles, does move a step towards our approach, which is outlined below.

The price-cost margin (PCM) function is given by the ratio $-\frac{\theta_t}{\alpha_1}$, and can be derived from the equation: $\beta_3 I_t = -\ln(1 + \theta_t/\alpha_1)$. Theory predicts that θ_t is higher during collusive regimes and that we should expect β_3 to be positive, as α_1 is expected to be negative. When I_t is known, using the *PO* cheating variable collected by Ulen (1979), Porter estimates Eqs. (8) and (9) using 2SLS. Identification comes from the fact that there is an explicit functional form, derived in Porter, for marginal costs, and that there are demand and pricing equations exogenous shifters. When I_t is unknown, a new variable is estimated using an endogenous switching (hidden) regime model, as in Lee and Porter (1984).¹⁰ This is the way that Porter constructs his *PN* binary variable. As outlined in the data section of this paper we use a *PR* binary variable, constructed from the Aldrich Report (1893), to reflect stability or not. This turns out to be similar to the estimated *PN* binary variable of Porter and will be shown in the empirical section to pick up the documented hidden regime in the pricing equation of Porter. Treating *PR* as data allows us to employ a two-step estimation procedure to be outlined below.

3.2 Our Extension of Porter

We employ a classic simultaneous equations model for demand and pricing equations. Pricing will be conditioned on the probability of the Cartel remaining in a collusive or stable regime.

Cartel Stability:

¹⁰In this case the demand and pricing equation error terms are assumed to be normally distributed.

To allow for persistence in regimes, we model Cartel stability as an ARMA(1,1) linear probability model

$$\begin{aligned}
PR_t &= \phi PR_{t-1} + \gamma_0 + \gamma_1 N_{t-1} + \gamma_2 L_{t-1} + \gamma_3 NWC_{t-1} + \gamma_4 NWO_{t-1} \\
&\quad + \gamma_5 ER_{t-1} + \gamma_6 EL_{t-1} + U_{3t} \\
U_{3t} &= \rho V_{t-1} + V_t.
\end{aligned} \tag{10}$$

In general the JEC sets rates to ensure that the ICC inside the cartel is binding. The results in Porter are replicated and accepted using our PR variable. PR set to zero represents finite periods of revisions. The interesting issue relates to what is triggering these revisions. We compare different theories against one another. Each theory provides us with a different reason for the ICC to change. If the JEC fails to adjust its rate optimally these factors can lead to a period of instability. As in Porter (1985) and Vasconcelos (2004) we account for the number of firms in the Cartel, N , and for the opening and closing of the Lakes as internal factors that may effect the ICC. We add external controls for the cumulated number of weeks that Lakes remain open, NWO , and the countdown on number of weeks until the Lakes re-open, NWC to control for the effect of anticipated deterministic cycles modeled in Haltiwanger and Harrington (1991). We also include the internal set of triggers, EL , used by Ellison, reflecting unusual movements in firm level market shares. Finally, we introduce our new variable that reflects errors in expectations of corn prices in New York, Eq. (7). Negative errors in expectations reflect a situation where the JEC is likely to have underestimated expected demand and overestimated price competition from outside transportation modalities. Clearly, the sub-optimal JEC rates can lead to an unstable ICC. We put forward unexpected commodity market shocks as the key factor that can threaten the Cartel's stability. The variable V_t denotes a mean zero error term.

Demand Equation:

We extend Porter's demand equation (8) in two ways. First, we expand the set of variables in the linear structure; most importantly we introduce the price of a substitute transportation mode. Secondly, we control for expected demand cycles using a nonparametric function. Ellison allows for hidden omitted variable regimes in demand and serial correlation in the demand residuals. We address this issues by including new control variables and add a lagged dependent variable in demand to allow for partial adjustments. The latter is done as a robustness test on our estimation results. The baseline demand equation that we estimate is:

$$q_t = \alpha_{0[t]} + \alpha_1 gr_t + \alpha_2 gr_t^{*E} + \alpha_3 L_t + \Omega_1(MNCY_t^E, NWC_t, NWO_t) + U_{1t}, \tag{11}$$

Equation (11) depends on the own grain transportation rate, gr_t , and on the expected rate of the outside transportation rates, gr_t^{*E} . L_t is a dummy equal to one when the Great Lakes are open to shipping, and zero otherwise. U_{1t} is a mean zero error term. Here the parameter $\alpha_{0[t]}$ includes a constant, month dummies and also year dummies. To control for expected deterministic demand cycles, not captured by our price variables, we also include the variables number of weeks to Lakes opening and Lakes open, NWC and NWO respectively, and the (expected) marginal net convenience yield (inventory stocks in New York), $MNCY$, in an unspecified Ω_1 function. We employ a semiparametric estimation set out in Appendix A and this will be done simultaneously with the pricing equation that we outline below.

Pricing Equation:

We enrich Porter's pricing equation (9) in two ways. First we include new variables. A second clear

point of departure is the absence of I_t , a dummy that equals one during a collusive regime, and zero otherwise. This is replaced with a Ω_2 function that will allow us back-out week to week dynamics in θ_t for a given set of demand primitives:

$$gr_t = \beta_{0[t]} + \beta_1 q_t + \beta_2 S_t + \Omega_2 [gr_t^{*E}, NWC_t, NWO_t, E_t (PR_{t+1})] + U_{2t}, \quad (12)$$

Having an estimate of $\Omega_2(\cdot)$ we can back-out the price-cost margin, $-\frac{\theta_t}{\eta}$, from the relation $\Omega_{2t} = -\ln(1 + \theta_t/\eta)$, where η is the total market elasticity, $\eta \equiv \alpha_1 + \alpha_2$. In other words, we model Porter's unobservable I_t with observables in a nonparametric form, $\Omega_2(\cdot)$, and not as a hidden binary regime. The observables used control for expected exogenous pricing cycles from external competition, gr^{*E} , NWC , NWO and for the predicted probability of Cartel stability r weeks ahead, $\hat{P}R_{t+r}$. We believe the latter is a good approximation to the way that Gallet and Schroeter (1995) empirically relate the mark-up at time t to the discounted expected value of future JEC collusive profits. We control for the effect on the mark-up of movements in expected future demand, as motivated by Haltiwanger and Harrington (1991), through NWC and NWO . We use NWC and NWO to proxy for expectations of demand.¹¹

The unspecified function $\Omega_2(\cdot)$ is aimed at catching the mark-up part of the pricing equation. We do not make any parametric assumption on $\Omega_2(\cdot)$ but rather exploit the data and model $\Omega_2(\cdot)$ nonparametrically. We include in the function all those variables that we think can affect directly, and interact with the other variables, to drive the mark-up. As in Porter, once we specify marginal costs as the sum of the error term and $\beta_{0[t]} + \beta_1 q_t + \beta_2 S_t$, the deterministic residual becomes a function of the mark-up. One disadvantage with this approach is that some of the controls for marginal cost could clearly be part of the mark-up. Hence we have to be careful about the interpretation of the level of the mark-up.

4 Results

Porter's Hidden Regime:

The 2SLS and ML columns 1-4 of Table 4 reproduce the results of Porter's Table 3. Columns 5-8 repeat the estimations, but replace his variable PO with our observed cheating variable, PR , constructed from the Aldrich Report. The main aim of this exercise is to see whether PR estimates the incidence of cheating similarly to the variable PN , endogenously estimated in Porter. Table 4 suggests that the use of PO or PR in general produces comparable results. There are differences worth mentioning however. The employment of PR , instead of PO , raises the R^2 in the pricing equation from 0.32 in column 2 to 0.67 in column 6, for the 2SLS results. This is lower than 0.78 in column 4 when the hidden regime is endogenously estimated using PO as the original variable. The same ML estimator can increase the R^2 to 0.85 in column 8 when using PR as the initial variable. The subsequent columns 9-16 are a rerun of the estimations in columns 1-8, with the addition of year dummies as controls in the demand equation. We see that controlling for year dummies in demand strengthens the explanatory power of the demand side. We run an independent two-sample Student's t-test and find that controlling for year dummies makes the estimated coefficients on the cheating dummy in the 2SLS estimators statistically different from one another, at the 5 per cent significance level. Also, the same test highlights a significant difference at the 1 per cent level in the estimated coefficients on the cheating dummy of the ML(PN) and

¹¹We capture exogenous movements in current demand using the price gr^{*E} , while month (and when applicable year) dummies and endogenous movements in current demand are accounted for through cost. NWC and NWO may just reflect week effects in current demand but the controls are consistent with and do control for the effects of expected demand.

2SLS(PR) estimators, inclusive or not of year dummies in demand. No significant difference is found for the estimated price elasticity variable. Hence the estimated level of price-cost margin may differ across specifications that originally use *PN* or *PR*. Yet, when we compare columns 11 and 12 (Porter’s *PN*) to columns 13 and 14, our 2SLS estimates using *PR* performs just as well. There will only be slight differences in the incidence of price wars. In Table 1 we report basic summary statistics for *PO*, *PN*, *PR* and *PRN*. While *PO* is very different from the others, *PN*, *PR* and *PRN* are very similar. Hence, our use of *PR* and inclusion of year dummies in the demand equation does not change the key Porter result. There is a hidden regime in the pricing equation that is clearly linked to the “price wars” that occurred intermittently in this Cartel. Therefore when we estimate our demand and pricing equations we need to condition on being in a regime of Cartel stability or not as defined by *PR*.

Causes of Cartel Instability:

The first four columns of Table 5 model our *PR* variable, which identifies periods of Cartel stability. We estimate the linear probability model with the ARMA (1,1) specification introduced in Eq. (10). The estimations highlight a strong persistence in the state of the dependent variable, as indicated by the high value of the ρ parameter. Once a shock brings the dependent variable from a state of stability to one of instability, it may take a certain number of weeks before it goes back to stability. The span of instability is embedded on the intensity of the shock that has caused the drifting away, and on realizations of other opposite (in sign) future shocks.

Another key variable that turns out significant in explaining Cartel stability is the error in expectations of the commodity price in New York introduced in Eq. (7). If the error pans out to be negative, then the spot price at time t in New York would prove to be higher than that expected at time $t - 1$. We have discussed earlier how that relates to the expected marginal net convenience yield and the expected outside transportation rate. Elevators will find out that inventories were below the optimal level and transportation companies will realize that freight rates could have been expected to be higher. The JEC will underestimate demand and formulate an expected rate of its competitors to be lower than it would have framed under certainty. In theory the JEC should have set a higher rate and transported more shipments to sustain the ICC constraint. This represents a clear mistake and potential loss in revenue for the Cartel and creates a higher probability of instability in the JEC. We find clear evidence that unexpected demand shocks in corn markets in New York triggered instability in the JEC. This is consistent with Green and Porter (1984) and is similar to a finding in Ellison (1994), who worked with the random part of the demand residual to model unexpected demand shocks. We have gone a step further and linked it to errors in expectations of corn market prices in New York. Anticipated demand cycles, the cumulated number of weeks that Lakes remain open, *NWO*, and the countdown on number of weeks until the Lakes re-open, *NWC*, which control for the effect of anticipated deterministic cycles modeled in Haltiwanger and Harrington (1991), are insignificant. This is also consistent with the findings of Ellison who used different endogenous indices to control for expected demand using the autocorrelated demand residuals, among other components. The same important result, that demand shocks and not anticipated cycles were the key drivers of Cartel instability, emerges. This supports the theory of Green and Porter (1984).

As in Porter (1985) and Vasconcelos (2004) we account for the number of firms in the Cartel, N , and for the opening and closing of the Lakes as factors effecting the ICC constraint. In contrast to them, the number of firms is never significant in our model, while the probability of Cartel instability is more likely to happen in the Lakes open regime. A feature of the Lakes open regime is that demand tends to be low for the JEC up to the harvesting and then increases rapidly up to Lakes closing. We will see that profits for the JEC, which we estimate post-regression analysis, were “normally” highest in the latest weeks of

Lakes open, when prices and shipments both increased. Errors in expectations about demand in this period, in particular setting price and shipments below the optimal level, would be very problematic for the Cartel. Finally, we include the set of triggers, EL , used in Ellison, and find as he did that unusual movements in market shares inside the JEC were not as important as the common external demand shocks that came from New York which all firms faced.

Estimating Mark-Ups and Profits:

We estimate mark-up and profit dynamics for the JEC using a classic simultaneous equations model for demand and pricing equations. Pricing will be conditioned on the probability of the Cartel remaining in a collusive, or stable, regime. We utilize the specification displayed in column 4 of Table 5 to compute the predicted probability of Cartel stability $\hat{P}R_{t+1}$, which we incorporate in our modeling of $\Omega_2(\cdot)$ in the regressions documented in Table 6.

In the 2SLS columns for the baseline model in Table 6, we linearize the $\Omega_2(\cdot)$ function in the pricing equation, and the $\Omega_1(\cdot)$ function in the demand equation. We can think of this as a polynomial of order one in the variables that enter the two functions. It has the advantage that it simplifies the estimator to a 2SLS approach which, given the use of year dummies, can be compared to the results documented in columns 13-14 in Table 4. We can judge whether these new control variables have interesting partial effects in terms of sign, magnitude and significance. The down side is that we are missing out on potentially interesting interactions between the variables in these functions. For example, our controls for deterministic cycles in $\Omega_2(\cdot)$, which are: gr^{*E} , NWC and NWO could impact JEC rate setting very differently when interacted with the predicted probability of Cartel stability, $\hat{P}R_{t+1}$. Hence we also estimate and document the results of using a semiparametric GMM estimation for this baseline model.

We now discuss the results for the baseline model. Our variable, gr^{*E} , that controls for the expected price on alternative modes of transportation, comes in significant in demand. An increase in the grain rate of the alternative modes of transportation increases demand for shipments by Cartel. This is an important result as it will drive, along with the JEC grain rate, the total market elasticity, $\eta \equiv \alpha_1 + \alpha_2$, which we need for calculating our price-cost margin. The variables in our $\Omega_1(\cdot)$, that control for anticipated demand, such as the (expected) marginal net convenience yield, $MNCY^E$, for inventories in New York, are not significant as independent partial effects. The prices are doing all the work in the equation.

In the pricing equation, all our new variables in $\Omega_2(\cdot)$ come in significant. All things equal, the accumulation of weeks to Lakes closing, NWO , puts an upward pressure on pricing and the loss of weeks to Lakes opening puts a downward pressure on prices, NWC . The expected price of the outside transportation options, gr^{*E} , creates an upward pressure on price. We see the JEC as a price follower in this optimal response function. The estimated probability of stability, $\hat{P}R_{t+1}$, comes in significant and has important upward pressure on pricing. The linearized $\Omega_2(\cdot)$ function can be backed out. There is no real change in the sign and significance of the other variables, except for output in pricing being positive and significant. The overall explanatory power of the supply side model is now higher, giving us increased confidence in our attempts to estimate the $\Omega_2(\cdot)$ function.

This baseline model is also estimated using a semiparametric GMM estimation method to allow $\Omega_2(\cdot)$ in pricing and the $\Omega_1(\cdot)$ in demand to be estimated nonparametrically. We adjust the Robinson (1988) Difference Estimator in order to account for the endogeneity in the system of simultaneous equations (see Appendix A for details on the estimator). The results from the semiparametric estimation for the baseline model are presented in the semiparametric columns of Table 6. The sum of the own- and cross-price elasticities are now estimated to be lower. The $\Omega_2(\cdot)$ function is computed to be a bigger deterministic component as the overall explanatory power of the supply side model has increased from

0.68 to 0.85, due to implicit interactions between the variables in the $\Omega_2(\cdot)$ function.

Ellison allows for serial correlation in the demand equation. To improve the overall explanatory power of the demand equation and get better estimates of price elasticities we model demand as a partial adjustment model. The structure in the demand equation suggests that we do not control for differences in actual rates (which change daily) and the official rate (set weekly) well enough and we should allow for a one week partial adjustment. Our results for this model using a 2SLS estimator of our linear modeling are presented in columns 5-6, and its semiparametric estimation is presented in columns 7-8, of Table 6. The parameters and standard errors have to be divided by $(1 - \hat{\beta}_{[q_{t-1}]})$ to be comparable to those of the baseline model. The explanatory power of the demand model is now 0.74. More importantly, we see that the sum of the “adjusted” own- and cross-price elasticities are higher when compared to the baseline model. Hence, our estimated mark-ups will be affected by the lagged dependent variable on the demand side. There are some changes on the pricing side. The linear modeling of $\Omega_2(\cdot)$ shows the expected outside transportation rate has a bigger and more significant effect. The estimated cheating probability has a smaller coefficient. Output in marginal cost is showing some economies of scale. Unlike the earlier literature, having controlled effectively for the omitted variables and partial adjustment, we now observe economies of scale in marginal costs.¹² While Fabra (2006) shows us that the results of Haltiwanger and Harrington (1991) would be less likely to hold in industries with capacity constraints, economies of scale theoretically reinforce the mechanisms in Haltiwanger and Harrington (1991).¹³ The explanatory power of the pricing equation increases further to 0.87 when estimated semiparametrically. Our $\Omega_2(\cdot)$ term will be estimated to be slightly different in the presence our partial adjustment model.

Our estimated mark-up dynamics are calculated using the estimated $\Omega_2(\cdot)$ in the pricing equation and η in demand equation from the four models documented in Table 6. The top four graphs of Figure 5 are plots of the estimated price-cost margin, $-\frac{\hat{\theta}_t}{\hat{\eta}}$, overlapped by their smoothed cycles, constructed from our four structural models of equilibrium pricing and demand. The estimates of the price-cost margin are plotted over the Lakes opening and closing periods, and against periods of Cartel instability as defined by our $PR=0$ variable.¹⁴ The bottom four graphs are the corresponding plots of estimated profit (overlapped by their smoothed cycles), constructed from our four structural models.¹⁵

The estimated cycles from our four models in Table 6 are reasonably similar in trends but differ in levels. Clearly, the weeks of Cartel instability are associated with unusually low mark-ups and profits for the Cartel. Railroads made losses over some spells when PR was zero. Our semiparametric estimation of the partial adjustment model of demand with supply would suggest that the Cartel actually incurred sustained losses during these periods. In periods of stability we do see some interesting “stylized” cycles emerging. In Lakes closed regimes we see price-cost margins drop as Lakes opening approaches. While mark-ups are low at the start of Lakes open they consistently rise over the period. More importantly, looking at profit cycles, the periods coming to the end of Lakes open normally generated the highest weekly profits for the Cartel. The race against the clock in inventory management normally induced increases on the outside transportation rates (captured by gr^{*E}), hence the volume of trade and the grain rate for the Cartel can both increase. Given that the JEC had higher monopolistic power during the Lakes closed regime, it is interesting to see profits peaking at the end of the Lakes open periods.

¹²Walters (1967) has surveyed estimates of cost function in 34 industries, and found evidence of constant or increasing returns to scale.

¹³When demand is expected to be high, then marginal costs are expected to be low. A threat of a revision to a zero profit becomes more binding as expected demand rises, and less binding as expected demand falls.

¹⁴Sub-figures 5(a) through (d) have been set on to share the same constant. That is, from the correspondent semiparametric estimation of $\hat{\Omega}_2(\cdot)$ we have subtracted the constant computed in the linearized semiparametric case (2SLS estimation).

¹⁵Cartel profit is computed as mark-up times quantity and is expressed in tens of thousands of dollars.

This highlights the role and the need to have data on the external pressures that come from inventory management in New York and pricing over the Lakes and Canals on the JEC.

Cyclical Nature of Mark-Ups:

A core contribution of this paper is to provide evidence of cyclical mark-ups over our documented deterministic demand cycles. We represent the smoothed price-cost margin and profit cycles against normalized output cycles in Figure 6. Can we see obvious counter or pro-cyclical movements of mark-ups with output? What emerges is that during periods of Cartel stability we see four Lakes open episodes where output and price-cost margin move up together as we move towards Lakes closing. This generates rising profits that peak just before the Lakes close. We also see that during periods of Cartel stability we have five Lakes closed episodes, where output is rising but price-cost margins are falling as we move closer to Lakes opening. Periods of instability are less clear-cut but look counter-cyclical. As Ellison points out, we are not asking the right question here. What we should be asking is whether our estimated mark-ups are supportive of the mechanisms in the theory of Haltiwanger and Harrington (1991). To test their theory during the collusive periods, we regress price-cost margins during upswings and price-cost margins during downturns on the number of firms and a quartic function of the demand business cycle. The results from the regression are plotted in Figure 7.¹⁶ The Haltiwanger and Harrington (1991) theory seems to be validated: for the same level of demand, the price (mark-up) is lower when the JEC is in a period of prolonged decline in demand, compared to coming into a period of prolonged increases in demand. This is powerful evidence that during periods of stability the JEC did price optimally over deterministic demand cycles creating interesting dynamics in mark-ups that reiterate those found in Borenstein and Shepard (1996). This is strong evidence that pricing in cartels react in a predictable way to anticipated seasonal cycles.

5 Conclusions

The use of theory and data from Coleman (2009) allows us to control for the expected rate of transportation in alternative modalities and unexpected commodity price shocks in New York. These variables have a tremendous impact on the modeling of price and quantity movements in the JEC. Analysis of the JEC data, without controlling for the transportation rates of grain over the Great Lakes and Canals from the dominant competitor, was always going to be problematic. We find that these additional variables were necessary to model demand primitives. The industry elasticity of demand is made up of an important cross-price, as well as an own-price, effect. These demand primitives are needed to construct the mark-up from the estimated nonparametric deterministic component (pricing over marginal cost) in the pricing equation. In addition, the expected price of transportation outside the JEC, because of harvesting and inventory management over the Great Lakes and Canals, has distinctive deterministic demand cycles for the Railroad Cartel to set prices against. In modeling pricing above our marginal cost nonparametrically, we find evidence that such external deterministic demand cycles do matter, in addition to an expected probability of Cartel stability. The latter is found to be triggered by unexpected commodity price shocks in New York rather than deterministic demand cycles. This is consistent with cartel breakdowns as modeled in Green and Porter (1984). We estimate the equilibrium price path semiparametrically, simultaneously to demand, and conditioned on the estimated expectation of cartel

¹⁶The spikes in the figures are due to the number of firms varying from three to five during the period. We have no spikes when there are four firms, we have decreasing spikes when we have five firms, and increasing spikes in case of three firms.

stability. Linear estimates of the parameters of marginal cost allow us to back-out the nonparametric function and, using our demand primitives, get our weekly estimates of the price-cost margin for the JEC.

Our controls for external deterministic demand cycles, lead us to estimate rich weekly mark-ups and profits cycles during periods of Cartel stability. For the same volume of sales, the mark-up in a prolonged boom (later weeks of Lakes open) tends to increase when compared to the mark-up coming into a prolonged recession (later weeks of Lakes closed). We find the JEC set prices over demand cycles in a way that supports the theoretical considerations in Haltiwanger and Harrington (1991). As highlighted in Borenstein and Shepard (1996), such cyclical pricing may be a way of detecting illegal pricing behavior in a modern day cartel.

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Table 1: Summary Statistics (Variables in alphabetical order)

Variable name	Definition	Obs.	Mean	sd	Min.	Max.
PORTER						
GR	The official grain rate, in dollars per 100 lbs.	328	0.246	0.067	0.125	0.400
L	Lakes dummy, reported as one when Lakes are open, zero otherwise.	328	0.573	0.495	0	1
PO	Cheating dummy as reported in the Railway Review and Chicago Tribune.	328	0.619	0.486	0	1
PN	Estimated cheating dummy.	328	0.750	0.434	0	1
Q	Total quantity of grain shipped, in tons.	328	25,384	11,632	4,810	76,407
S_1	Dummy equal one from week 28 in 1880 to week 10 in 1883, zero otherwise. This period reflects the opening of a new line by Grand Trunk Railway.	328	0.424	0.495	0	1
S_2	Dummy equal one from week 11 in 1883 to week 25 in 1883, zero otherwise. This period reflects the opening of a new line by New York Central.	328	0.046	0.209	0	1
S_3	Dummy equal one from week 26 in 1883 to week 11 in 1886, zero otherwise. This period reflects the entry of Chicago and Atlantic Railways.	328	0.433	0.496	0	1
S_4	Dummy equal one from week 12 in 1886 to week 16 in 1886, zero otherwise. This period reflects the departure of Chicago and Atlantic Railways.	328	0.015	0.123	0	1
ELLISON[†]						
N	Number of firms (railroads)	328	4.351	0.627	3	5
BIG1	Unusually high market share of one firm (measure 1).	327	1.072 [1.091]	0.548 [0.569]	0.130 [0.040]	3.156 [2.971]
BIG2	Unusually high market share of one firm (measure 2).	327	1.141 [1.241]	0.680 [0.710]	0.169 [0.185]	3.975 [4.235]
BIGQ	Unusually high market share of one firm (measure 3).	327	1.971 [1.174]	0.945 [0.516]	-0.148 [0.158]	4.888 [2.973]
SMALL1	Unusually small market share of one firm.	327	1.139 [1.230]	0.700 [0.737]	0 [0.116]	6.116 [5.757]

[†] In square bracket the values computed by Ellison. Due to a different way of averaging over the first twelve weeks, our reproduction of Ellison's variables is slightly off from the original.

Table 1: Summary Statistics (Cont.)

Variable name	Definition	Obs.	Mean	sd	Min	Max
OUR CONSTRUCTED VARIABLES						
\widehat{BCQ}	Estimated Output Business Cycle (estimated using Hodrick and Prescott's (1997) filter).	328	25,384	6,973	10,517	41,485
ER	Error in expectations. Recovered from the difference between GP0N lagged one period and GPN.	320	-0.008	0.058	-0.393	0.554
GPC	Chicago spot (call) corn prices (New York Times). [†]	328	0.889	0.209	0.603	1.482
GP1C	Chicago future corn prices for delivery next month (next 4 weeks), New York Times. [†]	328	0.880	0.202	0.594	1.424
GPN	New York spot (call) corn prices (New York Times). [†]	328	1.105	0.187	0.817	1.946
GP0N	New York future corn prices for delivery within the month (New York Times). [†]	320	1.097	0.186	0.815	1.964
GP1N	New York future corn prices for delivery next month (next 4 weeks), (New York Times). [†]	328	1.084	0.178	0.817	1.572
GP2N	New York future corn prices for delivery in two months (in 8 weeks), (New York Times). [†]	328	1.082	0.180	0.817	1.574
GR*	Proxy for transportation rates of competitors $\equiv (GP0N - GPC)$.	320	0.208	0.085	0.010	0.750
GRAIL	Grain rate of transport by All Railroads in dollars per 100 lbs (Aldridge's report). Available for the period 1878-91.	328	0.254	0.059	0.140	0.400
GRLC	Grain rate of transport by Lakes and Canals in dollars per 100 lbs (Aldridge's report). Available for the period 1878-83.	138	0.153	0.046	0.063	0.288
GRLR	Grain rate of transport by Lakes and Railroads in dollars per 100 lbs (Aldridge's report). Available for the period 1878-91.	190	0.185	0.044	0.110	0.295
LC	Lakes and Canals dummy, reported one when $GRLC > 0$, zero otherwise.	138	0.421	0.494	0	1
LR	Lakes and Railroads dummy, reported one when $GRLR > 0$, zero otherwise.	190	0.579	0.494	0	1
MNCY ^E	Proxy for (expected) Marginal Net Convenience Yield $\equiv (GPN - GP0N)$.	320	0.010	0.020	-0.045	0.123
NWC	Yearly de-cumulative Number of Weeks to the opening of Lakes (zero when open).	328	4.159	6.282	0	23
NWO	Yearly cumulative Number of Weeks the Lakes remain Open (zero when closed).	328	9.311	10.636	0	34
PR	A dummy equal one if the JEC grain rate was equal to the Chicago-New York grain rate that Railroads, including the JEC, tried to peg to; zero otherwise (Aldridge's report).	328	0.765	0.424	0	1
PRN	Estimated PR dummy.	328	0.759	0.428	0	1

[†] Weekly average of daily prices, where a daily price is the average of the minimum and maximum price of the day.

Table 2: Number of Weeks Lakes Open L, Lakes and Railroads Open LR, Lakes and Canals Open LC. Number of Weeks of Collusion based on PO and PR

Year	N. Weeks	L	LR	LC	PO	PN	PR	PRN
1880	52	34	33	33	52	52	51	52
1881	52	28	29	26	15	26	26	26
1882	52	33	35	32	48	41	40	41
1883	52	33	31	27	47	52	49	52
1884	52	31	32	.	22	33	26	33
1885	52	29	30	.	12	26	24	29
1886	16	0	0	.	7	16	15	16
Tot.	328	188	190	118	203	246	251	249

Table 3: Correlations

	GR	GRLC	GRLR	GR*
GR	1.00 (328)			
GRLC	0.65 [†] (138)	1.00 (138)		
GRLR	0.79 [†] (190)	0.86 [†] (137)	1.00 (190)	
GR*	0.65 [†] (320)	0.81 [†] (135)	0.62 [†] (187)	1.00 (320)

In bracket number of observations.

[†] Significant at 1%.

Table 4: Replicating Porter using PO and PR

VARIABLES	No Year Dummies												Year Dummies																					
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16		
	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†	2SLS(PO)	ML(PN)†	2SLS(PR)	ML(PN)†		
C	9.177*** (0.184)	-3.975** (1.778)	8.987*** (0.150)	-4.093*** (1.152)	9.140*** (0.166)	-1.458 (1.033)	9.103*** (0.145)	-1.586** (0.806)	8.745*** (0.302)	-3.000*** (0.725)	9.311*** (0.139)	-3.785*** (1.088)	8.312*** (0.236)	-1.883*** (0.514)	9.200*** (0.122)	-1.362 (0.910)																		
L	-0.437*** (0.120)	-0.735*** (0.119)	-0.459*** (0.118)	-0.434*** (0.120)	-0.434*** (0.120)	-0.449*** (0.118)	-0.449*** (0.118)	-0.449*** (0.118)	-0.415*** (0.104)	-0.549*** (0.103)	-0.549*** (0.103)	-0.549*** (0.103)	-0.434*** (0.104)	-0.434*** (0.104)	-0.400*** (0.098)	-0.400*** (0.098)																		
gr	-0.735*** (0.119)	-0.881*** (0.090)	-0.881*** (0.090)	-0.762*** (0.105)	-0.762*** (0.105)	-0.805*** (0.088)	-0.805*** (0.088)	-0.805*** (0.088)	-0.629*** (0.191)	-0.740*** (0.084)	-0.740*** (0.084)	-0.740*** (0.084)	-0.925*** (0.141)	-0.925*** (0.141)	-0.804*** (0.077)	-0.804*** (0.077)																		
S1	-0.201*** (0.055)	-0.198*** (0.037)	-0.198*** (0.037)	-0.198*** (0.037)	-0.230*** (0.038)	-0.230*** (0.038)	-0.230*** (0.038)	-0.161*** (0.028)	-0.201*** (0.050)	-0.201*** (0.050)	0.024 (0.041)	0.024 (0.041)	-0.232*** (0.039)	-0.232*** (0.039)	-0.025 (0.034)	-0.025 (0.034)																		
S2	-0.173*** (0.081)	-0.234*** (0.047)	-0.234*** (0.047)	-0.234*** (0.047)	-0.163*** (0.056)	-0.163*** (0.056)	-0.163*** (0.056)	-0.193*** (0.036)	-0.172** (0.074)	-0.172** (0.074)	0.036 (0.072)	0.036 (0.072)	-0.162*** (0.057)	-0.162*** (0.057)	0.045 (0.058)	0.045 (0.058)																		
S3	-0.319*** (0.065)	-0.369*** (0.048)	-0.369*** (0.048)	-0.369*** (0.048)	-0.395*** (0.047)	-0.395*** (0.047)	-0.395*** (0.047)	-0.304*** (0.033)	-0.302*** (0.047)	-0.302*** (0.047)	-0.033 (0.073)	-0.033 (0.073)	-0.406*** (0.073)	-0.406*** (0.073)	0.002 (0.059)	0.002 (0.059)																		
S4	-0.208 (0.172)	-0.336*** (0.076)	-0.336*** (0.076)	-0.336*** (0.076)	-0.325*** (0.113)	-0.325*** (0.113)	-0.325*** (0.113)	-0.212*** (0.038)	-0.0973** (0.124)	-0.0973** (0.124)	-0.194* (0.111)	-0.194* (0.111)	-0.295*** (0.096)	-0.295*** (0.096)	0.063 (0.087)	0.063 (0.087)																		
PO	0.368*** (0.054)	0.627*** (0.056)	0.627*** (0.056)	0.627*** (0.056)	0.420*** (0.040)	0.420*** (0.040)	0.420*** (0.040)	0.526*** (0.035)	0.344*** (0.034)	0.344*** (0.034)	0.688*** (0.054)	0.688*** (0.054)	0.434*** (0.029)	0.434*** (0.029)	0.589*** (0.047)	0.589*** (0.047)																		
PN																																		
PR																																		
PRN																																		
q	0.253 (0.173)	YES	0.242** (0.112)	YES	0.011 (0.101)	YES	0.158** (0.070)	YES	0.158** (0.070)	YES	0.188* (0.104)	YES	0.052 (0.050)	YES	0.589*** (0.047)	YES																		
Month Dummies	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO
Year Dummies	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328	328
Obs.	0.310	0.316	0.302	0.280	0.308	0.270	0.308	0.2854	0.518	0.431	0.498	0.715	0.515	0.654	0.517	0.517																		
R ²																																		

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

†Uses the Switching Regression Model described in Lee and Porter (1984).

Table 5: ARMA (1,1) Cartel stability estimations

VARIABLES	PR (=1 Collusion)			
C	1.605 (2.979)	1.587 (2.969)	1.662 (3.019)	1.714 (3.019)
N_{t-1}	-0.054 (0.076)	-0.057 (0.076)	-0.045 (0.073)	-0.053 (0.077)
L_{t-1}	-0.308* (0.185)	-0.302 (0.188)	-0.311* (0.186)	-0.317* (0.181)
NWO_{t-1}	0.006 (0.010)	0.006 (0.010)	0.006 (0.010)	0.007 (0.010)
NWC_{t-1}	-0.003 (0.011)	-0.002 (0.012)	-0.003 (0.012)	-0.003 (0.012)
ER_{t-1}	0.561*** (0.218)	0.571*** (0.215)	0.569*** (0.218)	0.564*** (0.213)
$BIG1_{t-1}$	0.024 (0.034)			
$BIG2_{t-1}$		0.028 (0.023)		
$BIGQ_{t-1}$			-0.017 (0.025)	
$SMALL1_{t-1}$				0.045* (0.026)
PR_{t-1}	0.791*** (0.051)	0.788*** (0.051)	0.787*** (0.052)	0.797*** (0.051)
V_{t-1}	0.045 (0.067)	0.047 (0.066)	0.049 (0.065)	0.026 (0.068)
Month Dummies	NO	NO	NO	NO
Year Dummies	NO	NO	NO	NO
Obs.	318	318	318	318
R^2	316/318	316/318	316/318	316/318
Obs. $\hat{P}R < 0$	1/318	1/318	1/318	1/318
Obs. $\hat{P}R > 1$	52/318	49/318	50/318	59/318
ll	-10.305	-9.725	-10.420	-8.478

Robust standard error in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
We employ an optimization method that switches between the BHHH
and the BFGS algorithm.

Table 6: Estimations

VARIABLES	Baseline Model				Partial Adjustment Model [†]			
	Linear 2SLS		Semiparametric GMM		Linear 2SLS		Semiparametric GMM	
	1 q	2 gr	3 q	4 gr	5 q	6 gr	7 q	8 gr
C	8.493*** (0.421)	-2.477*** (0.502)			2.898*** (0.465)	-1.132*** (0.330)		
L_t	-0.582*** (0.122)		0.119 (0.457)		-0.284*** (0.093)		0.149 (0.345)	
NWC_t	-0.013 (0.013)	0.023*** (0.006)			-0.005 (0.009)	0.022*** (0.006)		
NWO_t	0.012 (0.009)	0.018*** (0.004)			0.013* (0.007)	0.016*** (0.004)		
$MNCY_t^E$	-0.402 (1.054)				0.181 (0.769)			
gr_t	-1.094*** (0.195)		-0.774*** (0.184)		-0.572*** (0.160)		-0.426** (0.166)	
gr_t^{*E}	0.120** (0.059)	0.095* (0.052)	0.092* (0.051)		0.089** (0.044)	0.107*** (0.023)	0.072* (0.038)	
q_t		0.079* (0.047)		0.051 (0.043)		-0.049* (0.029)		-0.045 (0.033)
q_{t-1}					0.632*** (0.049)		0.603*** (0.063)	
$\hat{P}R_{t+1}$		0.439*** (0.036)				0.396*** (0.032)		
S_{1t}		-0.228*** (0.042)		0.005 (0.022)		-0.227*** (0.040)		0.005 (0.020)
S_{2t}		-0.143** (0.057)		0.065** (0.029)		-0.144*** (0.054)		0.064** (0.029)
S_{3t}		-0.374*** (0.045)		-0.053** (0.023)		-0.345*** (0.042)		-0.030 (0.020)
S_{4t}		-0.254** (0.098)		0.082 (0.056)		-0.331*** (0.091)		0.017 (0.044)
Month Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	NO	YES	NO	YES	NO	YES	NO
Obs.	311	311	311	311	311	311	311	311
R^2	0.510	0.680	0.561	0.849	0.738	0.711	0.743	0.872

Standard error in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[†] Coefficients and standard errors have to be divided by $\frac{1}{(1-\hat{\beta}_{q_{t-1}})}$ to be comparable to those of the baseline model,

where $\hat{\beta}_{q_{t-1}}$ is the estimated coefficient of q_{t-1} .

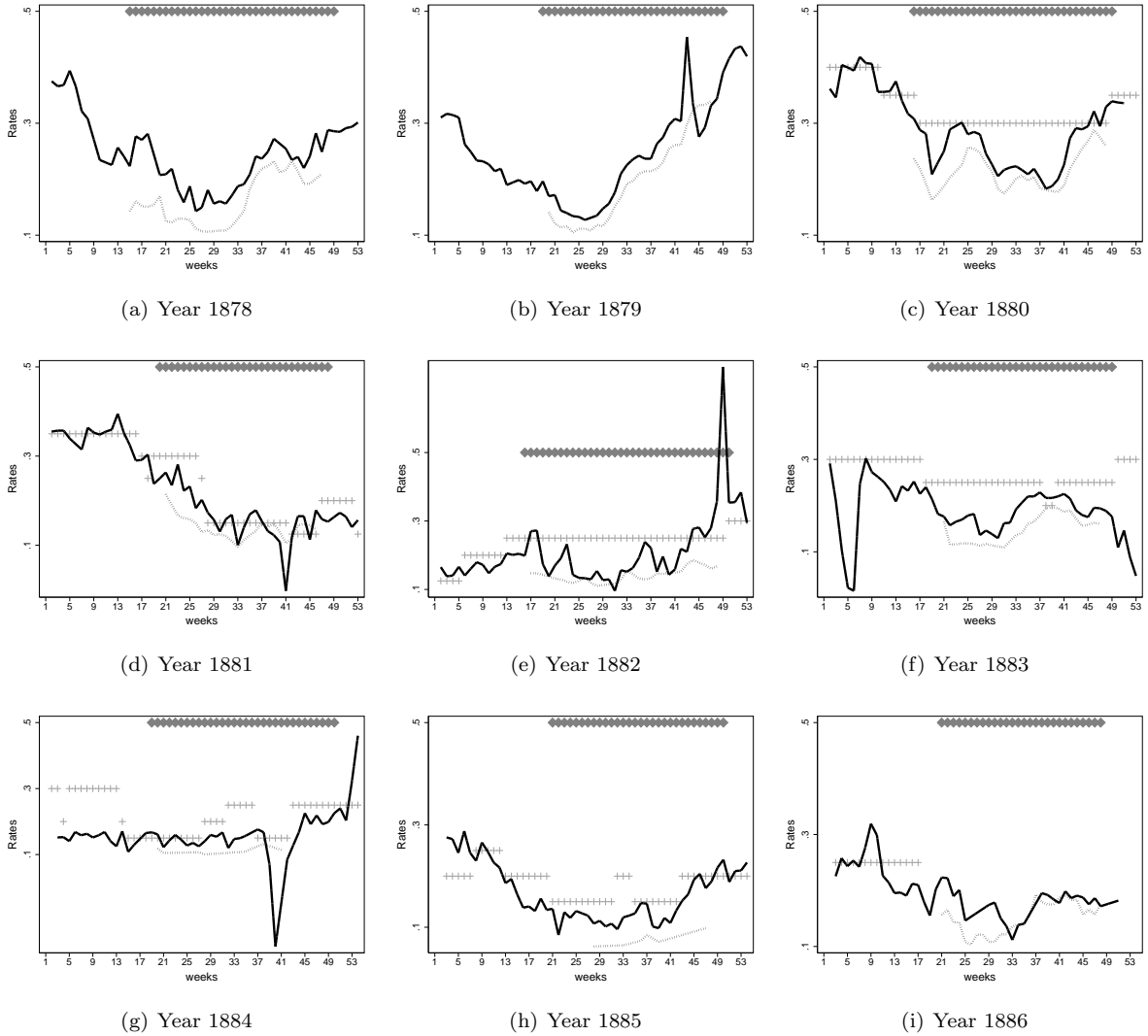


Figure 1: Modes of transportation rates: Lakes and Canals (GRLC \dots), JEC Railroads (GR +), Expected Outside Option (GR*E ---), the signs at .5 denote Lakes open (L=1)

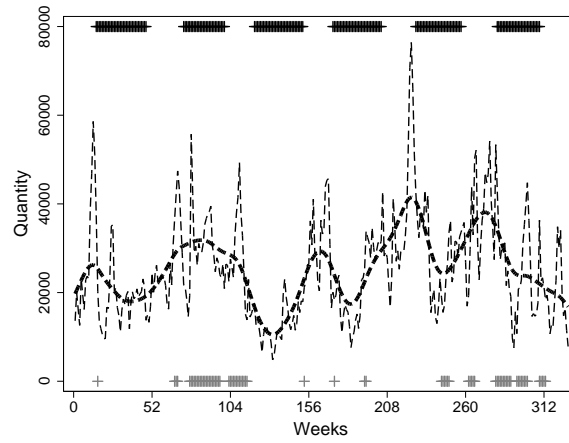


Figure 2: Quantity (---) and estimated quantity business cycles (—). The signs at 0 denote Cartel instability ($PR=0$); the signs at 80000 denote Lakes open ($L=1$)

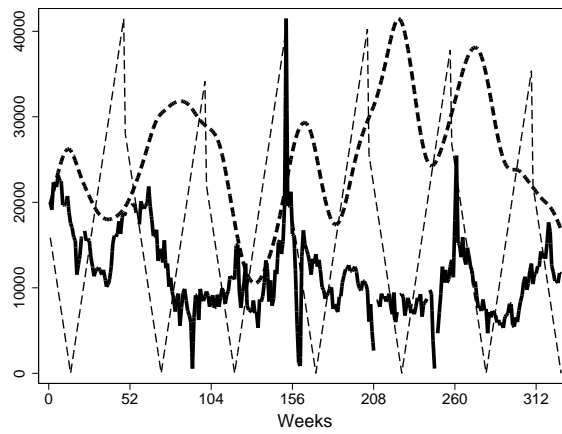


Figure 3: Estimated quantity business cycles (bold font ---), Number of weeks Lakes open/closed (---), Rate outside transportation options (—)

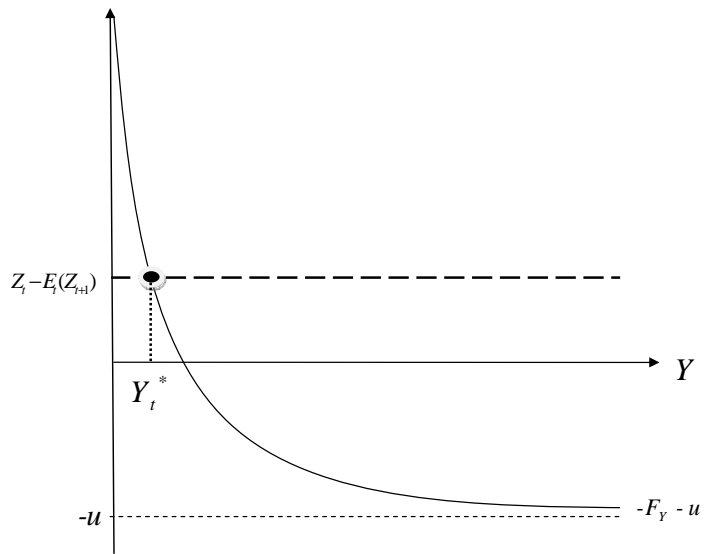


Figure 4: Marginal Net Convenience Yield Function

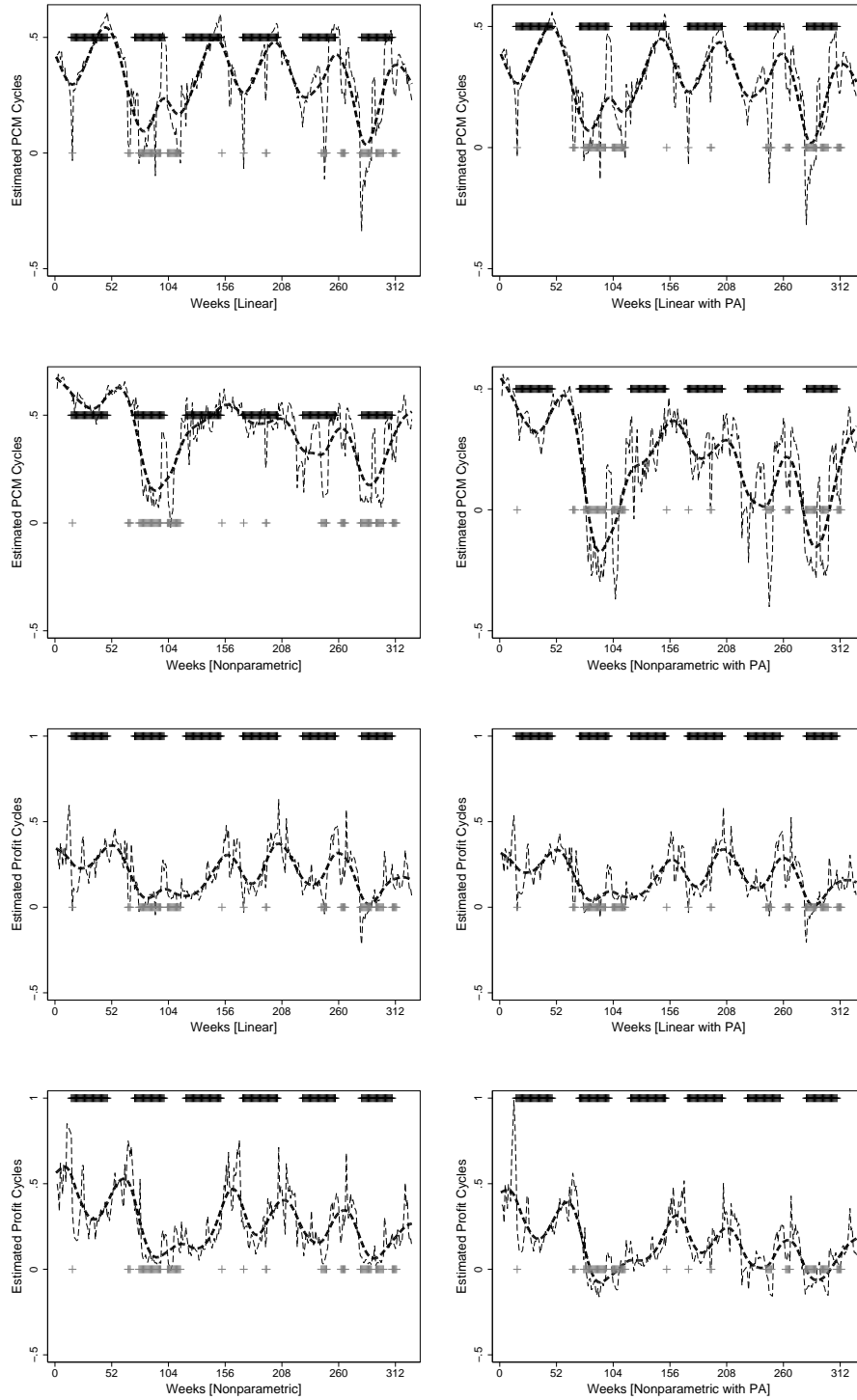


Figure 5: Estimated price-cost margin and profit (---), and estimated price-cost margin and profit business cycles (—). The signs at 0 denote Cartel instability ($PR=0$); the signs at .5 or 1 denote Lakes open ($L=1$)

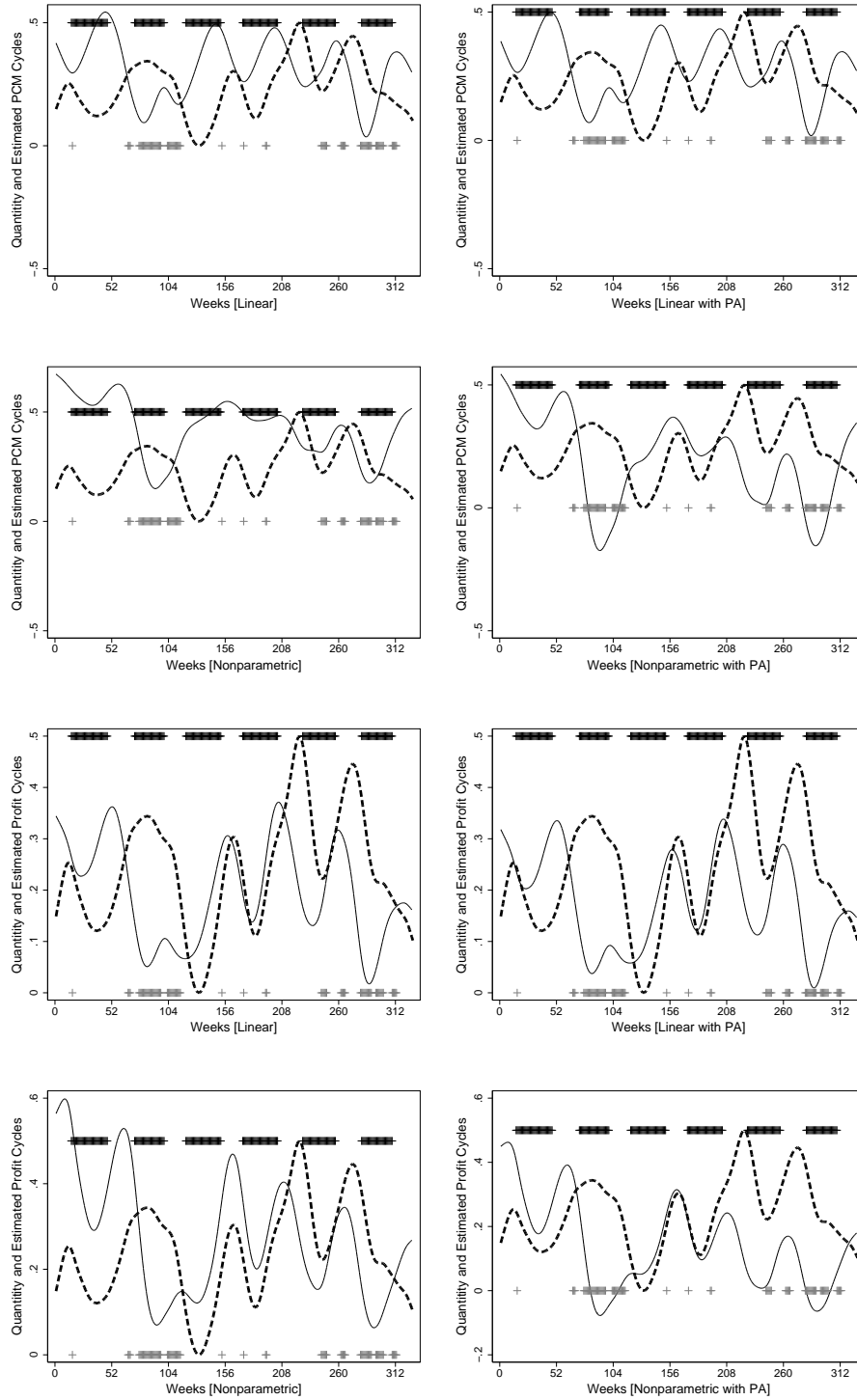


Figure 6: Normalized quantity business cycles (---), and estimated price-cost margin and profit business cycles (—). The signs at 0 denote Cartel instability ($PR=0$); the signs at .5 denote Lakes Open ($L=1$)

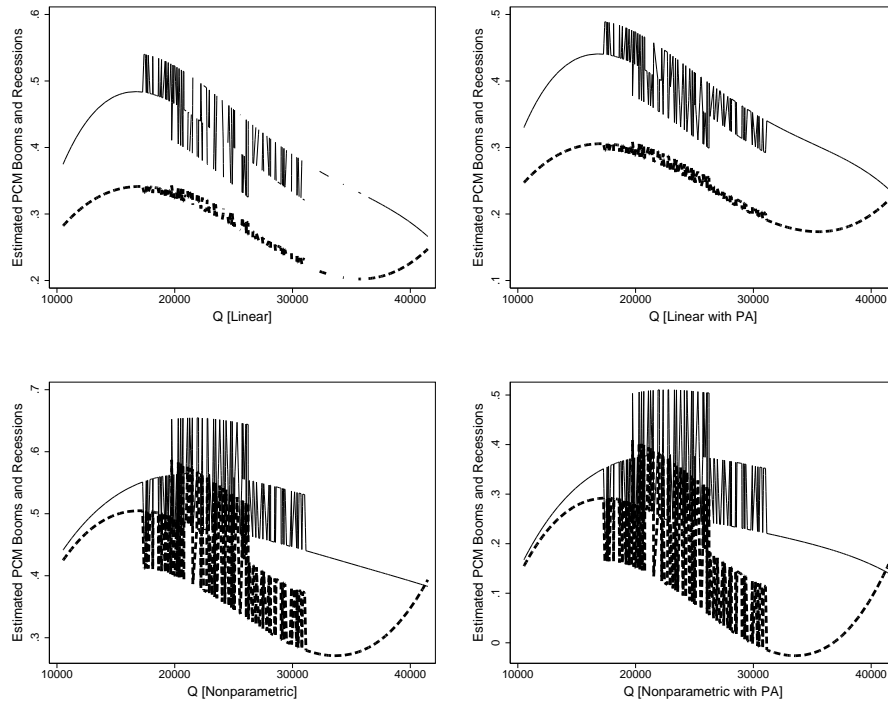


Figure 7: Estimated price-cost margin booms (—) and price-cost margin recessions (---) by quantity business cycle and number of firms

A Econometrics

We specify the system of simultaneous equations to be of the following semiparametric form

$$\begin{aligned} q_t &= \mathbf{X}_{1t}^L \boldsymbol{\alpha} + \Omega_1(\mathbf{X}_{1t}^{NL}) + U_{1t} \\ gr_t &= \mathbf{X}_{2t}^L \boldsymbol{\beta} + \Omega_2(\mathbf{X}_{2t}^{NL}) + U_{2t}, \end{aligned} \quad (13)$$

with

$$\begin{aligned} \mathbf{X}_{1t}^L &\equiv \{\mathbf{C}_{1[t]}, [gr_t], gr_t^{*E}, L_t\} \\ \mathbf{X}_{2t}^L &\equiv \{\mathbf{C}_{2[t]}, [q_t], \mathbf{S}_t\} \\ \mathbf{X}_{1t}^{NL} &\equiv \{MNCY_t^E, NWC_t, NWO_t\} \\ \mathbf{X}_{2t}^{NL} &\equiv \{gr_t^{*E}, NWC_t, NWO_t, E_t(PR_{t+1})\}. \end{aligned} \quad (14)$$

The terms $\mathbf{C}_{1[t]}$ and $\mathbf{C}_{2[t]}$ are in bold font and have time subscripts in square brackets as they include, month and year dummies, the former, and only month dummies, the latter. The constant is omitted both from \mathbf{X}_{1t}^L and \mathbf{X}_{2t}^L as it cannot be identified separately from the unknown nonparametric functions $\Omega_1(\cdot)$ and $\Omega_2(\cdot)$. Also, the variable $E_t(PR_{t+1})$ being unobserved at time t , we replace it with its predicted value $\hat{P}R_{t+1}$, which is a one period lead of the estimated $ARMA(1, 1)$ latent specification

$$\begin{aligned} PR_t &= \phi PR_{t-1} + \mathbf{X}_{3,t-1}^L \boldsymbol{\gamma} + U_{3t} \\ U_{3t} &= \rho V_{t-1} + V_t \end{aligned} \quad (15)$$

where,

$$\mathbf{X}_{3,t-1}^L \equiv \{C, ER_{t-1}, EL_{t-1}, L_{t-1}, N_{t-1}, NWC_{t-1}, NWO_{t-1}\}.$$

The estimated value of Equation (15) is

$$\hat{P}R_t = \hat{\phi} PR_{t-1} + \mathbf{X}_{3,t-1}^L \hat{\boldsymbol{\gamma}} + \hat{\rho} \hat{V}_{t-1}, \quad (16)$$

and its one-period lead is

$$\hat{P}R_{t+1} = \hat{\phi} PR_t + \mathbf{X}_{3t}^L \hat{\boldsymbol{\gamma}} + \hat{\rho} \hat{V}_t. \quad (17)$$

The system of equations (13) is on the whole identified via exogenous demand shifters (a Lakes open/closed dummy, year dummies that account for years of abundant/scarce crop and marginal net convenience yield to explain spikes in demand) and cost shifters (structural dummies). However, given that $E_t(PR_{t+1})$ is a term of \mathbf{X}_{2t}^{NL} we need to investigate the identification, further. Prior to providing any additional discussion on this matter, we recall that the unobserved $E_t(PR_{t+1})$ is replaced by the predicted value $\hat{P}R_{t+1}$. With such a formulation we hope that a one-period lead of the estimated PR series, $\hat{P}R$, displays less correlation with the U_2 series, than does the original PR series. In addition, the series is expected to exhibit no correlation or, if any, a minimal correlation, with the demand error term, U_1 . With this in mind, we add $\hat{P}R_{t+1}$ to the cost shifters and better identify the grain rate endogenous variable, gr .

We now generalize the above notation and denote with G the total number of equations, and with g one of these equations. Part of the notation that follows is inherited from Wooldridge (2002). For each equation g we assume that we have a set of instruments that satisfies the following condition

$$E(U_g | \mathbf{Z}_g) = 0, \quad g = 1, \dots, G. \quad (18)$$

We rewrite the system of simultaneous equations (13) in compact form as

$$\mathbf{y}_t \equiv \begin{pmatrix} q_t \\ gr_t \end{pmatrix}, \quad \mathbf{X}_t^L \equiv \begin{pmatrix} \mathbf{X}_{1t}^L & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_{2t}^L \end{pmatrix}, \quad \boldsymbol{\theta} \equiv \begin{pmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{pmatrix}, \quad \mathbf{U}_t \equiv \begin{pmatrix} U_{1t} \\ U_{2t} \end{pmatrix},$$

$$\boldsymbol{\Omega}(\mathbf{X}_t^{NL}) \equiv \begin{pmatrix} \Omega_1(\mathbf{X}_{1t}^{NL}) \\ \Omega_2(\mathbf{X}_{2t}^{NL}) \end{pmatrix}. \quad (19)$$

So that we have

$$\mathbf{y}_t = \mathbf{X}_t^L \boldsymbol{\theta} + \boldsymbol{\Omega}(\mathbf{X}_t^{NL}) + \mathbf{U}_t. \quad (20)$$

We employ the Robinson (1988) difference estimator to estimate Eq. (20). We take the expectation of Eq. (20) conditional on \mathbf{X}_t^{NL} and subtract it from equation (20) to get

$$[\mathbf{y}_t - \mathbf{E}(\mathbf{y}_t | \mathbf{X}_t^{NL})] = [\mathbf{X}_t^L - \mathbf{E}(\mathbf{X}_t^L | \mathbf{X}_t^{NL})] \boldsymbol{\theta} + \mathbf{U}_t, \quad (21)$$

where we made use of the assumption $\mathbf{E}(\mathbf{U}_t | \mathbf{X}_t^{NL}) = \mathbf{0}$.

Next, defining $\tilde{\mathbf{y}}_t \equiv [\mathbf{y}_t - \mathbf{E}(\mathbf{y}_t | \mathbf{X}_t^{NL})]$ and $\tilde{\mathbf{X}}_t^L \equiv [\mathbf{X}_t^L - \mathbf{E}(\mathbf{X}_t^L | \mathbf{X}_t^{NL})]$, Eq. (21) simplifies to

$$\tilde{\mathbf{y}}_t = \tilde{\mathbf{X}}_t^L \boldsymbol{\theta} + \mathbf{U}_t. \quad (22)$$

Given the matrix \mathbf{X}_t^L includes endogenous variables, one needs to deal with the endogeneity in a semi-parametric framework. As previously mentioned, we postulate that we have a set of instruments that satisfy condition (18). We write those instruments in compact form as

$$\mathbf{Z}_t \equiv \begin{pmatrix} \mathbf{Z}_{1t} & \mathbf{0} \\ \mathbf{0} & \mathbf{Z}_{2t} \end{pmatrix}, \quad (23)$$

with,

$$\begin{aligned} \mathbf{Z}_{1t} &\equiv \{C, \mathbf{C}_{1[t]}, gr_t^{*E}, L_t, \hat{P}R_{t+1}, \mathbf{S}_t\} \\ \mathbf{Z}_{2t} &\equiv \{C, \mathbf{C}_{2[t]}, \mathbf{S}_t, L_t, MNCY_t^E\}. \end{aligned} \quad (24)$$

Next, we adjust the Robinson (1988) difference estimator to deal with the endogeneity. So, we pre-multiply both sides of equation (22) by the transpose of the matrix of instruments, \mathbf{Z}_t , and get

$$\mathbf{Z}_t' \tilde{\mathbf{y}}_t = \mathbf{Z}_t' \tilde{\mathbf{X}}_t^L \boldsymbol{\theta} + \mathbf{Z}_t' \mathbf{U}_t. \quad (25)$$

Since both $\mathbf{E}(\mathbf{y}_t | \mathbf{X}_t^{NL})$ and $\mathbf{E}(\mathbf{X}_t^L | \mathbf{X}_t^{NL})$ are unknown, $\tilde{\mathbf{y}}_t$ and $\tilde{\mathbf{X}}_t^L$ are themselves unknown. We make use of our data and utilize the Hayfield and Racine (2008) `np` package developed in R to estimate $\mathbf{E}(\mathbf{y}_t | \mathbf{X}_t^{NL})$ and $\mathbf{E}(\mathbf{X}_t^L | \mathbf{X}_t^{NL})$ nonparametrically.¹⁷ In this way we recover the estimated values $\hat{\mathbf{E}}(\mathbf{y}_t | \mathbf{X}_t^{NL})$ and $\hat{\mathbf{E}}(\mathbf{X}_t^L | \mathbf{X}_t^{NL})$. Now, if we define $\hat{\tilde{\mathbf{y}}}_t \equiv [\mathbf{y}_t - \hat{\mathbf{E}}(\mathbf{y}_t | \mathbf{X}_t^{NL})]$ and $\hat{\tilde{\mathbf{X}}}_t^L \equiv [\mathbf{X}_t^L - \hat{\mathbf{E}}(\mathbf{X}_t^L | \mathbf{X}_t^{NL})]$, Equation (25) reduces to

$$\mathbf{Z}_t' \hat{\tilde{\mathbf{y}}}_t = \mathbf{Z}_t' \hat{\tilde{\mathbf{X}}}_t^L \boldsymbol{\theta} + \mathbf{Z}_t' \mathbf{U}_t. \quad (26)$$

¹⁷For the continuous variables (q , q_{-1} , gr , gr^*), we employ the Hurvich, Simonoff, and Tsai (1998) Kullback-Leibler Cross-Validation method, implemented in the function `npregbw`, to select the bandwidth for the multivariate Kernel regression `npreg`. For the dichotomous variables (month, year, Lakes and structural dummies), we utilize the Klein and Spady (1993) Single Index Model methodology, built in the function `npindexbw`, to pick the bandwidth for the regression `npindex`. The covariates retained for the demand and pricing equations are, respectively, \mathbf{X}_1^{NL} and \mathbf{X}_2^{NL} . Refer to Li and Racine (2007) for details on the nonparametric regression theory.

We now employ a GMM estimator with an optimal weighting matrix and estimate the linear parameters $\boldsymbol{\theta}$. This requires, first to estimate Eq. (26) by a 2SLS estimator

$$\hat{\boldsymbol{\theta}}_{2SLS} = \left[\hat{\mathbf{X}}' \mathbf{Z} (\mathbf{Z}' \mathbf{Z})^{-1} \mathbf{Z}' \hat{\mathbf{X}} \right]^{-1} \hat{\mathbf{X}}' \mathbf{Z} (\mathbf{Z}' \mathbf{Z})^{-1} \mathbf{Z}' \hat{\mathbf{y}}, \quad (27)$$

where the bold letters without time subscript are stacked matrices, e.g. \mathbf{Z} is

$$\mathbf{Z} \equiv \begin{bmatrix} \mathbf{Z}_1 \\ \dots \\ \mathbf{Z}_t \\ \dots \\ \mathbf{Z}_T \end{bmatrix}. \quad (28)$$

We use the estimated parameters $\hat{\boldsymbol{\theta}}_{2SLS}$ to compute the residuals, as these are necessary for the construction of the optimal weighting matrix estimator

$$\hat{\mathbf{W}} = \left(\sum_{t=1}^T \mathbf{Z}'_t \hat{\mathbf{u}}_{t,2SLS} \hat{\mathbf{u}}'_{t,2SLS} \mathbf{Z}_t \right)^{-1}. \quad (29)$$

The GMM estimator is

$$\hat{\boldsymbol{\theta}}_{GMM} = \left[\hat{\mathbf{X}}' \mathbf{Z} \hat{\mathbf{W}} \mathbf{Z}' \hat{\mathbf{X}} \right]^{-1} \hat{\mathbf{X}}' \mathbf{Z} \hat{\mathbf{W}} \mathbf{Z}' \hat{\mathbf{y}}, \quad (30)$$

and the estimator for its asymptotic variance-covariance is

$$\mathbf{A} \hat{\mathbf{var}} \left(\hat{\boldsymbol{\theta}}_{GMM} \right) = \left[\hat{\mathbf{X}}' \mathbf{Z} \left(\sum_{t=1}^T \mathbf{Z}'_t \hat{\mathbf{u}}_{t,GMM} \hat{\mathbf{u}}'_{t,GMM} \mathbf{Z}_t \right)^{-1} \mathbf{Z}' \hat{\mathbf{X}} \right]^{-1}. \quad (31)$$

At last, the nonlinear component $\hat{\boldsymbol{\Omega}}$ is easily recovered as the difference

$$\hat{\boldsymbol{\Omega}}(\mathbf{X}_t^{NL}) = \hat{\mathbf{E}}(\mathbf{y}_t | \mathbf{X}_t^{NL}) - \hat{\mathbf{E}}(\mathbf{X}_t^L | \mathbf{X}_t^{NL}) \hat{\boldsymbol{\theta}}_{GMM}. \quad (32)$$