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Abstract

We present a method for analyzing the exercise of market power in an industry in which each firm produces multiple competing goods. We use the method to study the market power of refiners in Hawaii. These refiners sell in two principal markets: jet fuel, with a buyers consortium, and gasoline, with diffuse buyers. With data from January 1992 through the new millennium, we find significant evidence of the exercise of market power by refiners in the wholesale gasoline market. In contrast, we do not find evidence of market power by these refiners in the jet fuel market.

1 Introduction

Market power, and the abuse thereof, is a key question at the intersection of economics and policy making. Clear evidence of the exercise of market power in oligopolies is rare. Rather than smoking guns, we must usually settle for econometric evidence that is consistent with the exercise of power and (hopefully) inconsistent with alternative hypotheses. Such is the case in the Hawaiian refined products market (primarily gasoline and jet fuel). From 1992 to 2004, the wholesale price of gasoline was 20-70 cents per gallon higher in Hawaii than in Singapore, despite the fact that transportation from Singapore to Hawaii is estimated to be only 8 cents per gallon. A similar picture can be painted regarding prices in Los Angeles and Hawaii. In contrast, jet fuel prices were on average only 7 cents per gallon higher in Hawaii and, at times, lower priced than in Singapore. In 1998 the Hawaiian Attorney General filed suit against the two producers of refined products in Hawaii, Tesoro and Chevron/Texaco, alleging collusion in gasoline markets.
One of the classic models of pricing in an oligopoly is due to Green and Porter (1984). The authors develop a model of unobserved tacit collusion interspersed by price wars. Porter (1983) applies the model to railroad pricing in the 19th century. What is interesting about the paper is that there is no requirement that the firms collude completely, with complete information. In fact, it is imperfect coordination which generates price wars. The model does not provide unequivocal evidence of the exercise of market power; among other things, costs are not directly observed and must be disentangled from monopoly rents.

What is unique about the Hawaii case is that we have two joint products (gasoline and jet fuel), with one product sold into a clearly competitive market (jet fuel) and the other (gasoline) sold into a structurally less competitive market. This structure can help us better identify costs and thus infer monopoly rents.

That is the main contribution of this paper — to extend the Porter (1983) model of collusion with price wars to the case of joint products, with one product in a competitive market and the other possibly not. It is our view that this extension is an important one that can be useful in many other contexts.

In the next section we provide background on the Hawaiian market before presenting our extension of the price wars model. We then turn to the econometric implementation. Our results are consistent with tacit collusion in the Hawaiian gasoline market.

2 Hawaiian Refinery Production

Prior to 1962, civilian petroleum products were imported to Hawaii. In response to burgeoning air travel, the first refinery was opened in 1962, largely to meet the demand for jet fuel. Over the remainder of the decade, concern about monopoly power grew and the state subsidized the opening of a second refinery in 1970. Over the next twenty years, each refinery underwent technological upgrades and occasional changes of ownership, with no substantive impact on the market structure.

In 1995, the Hawaiian Fuel Facilities Corporation (HFFC) received approval to open an import terminal for jet fuel. The major buyers of jet fuel established the HFFC to create a foreign trade zone, so that US taxes would not be imposed on fuel used for flights to other countries. In 1997 the HFFC terminal opened followed in early 1998 by the opening of an import terminal for gasoline. The gasoline import terminal was jointly funded by Aloha and Texaco, two firms with extensive gasoline sales networks but no refining capacity.

Toward the end of 1998, the Hawaiian state attorney general filed suit against the two refinery owners (Chevron and Tesoro, at the time)
alleging anticompetitive behavior. The suit was settled in 2002, with the state receiving far less in damages than originally claimed. Perhaps in response, the state legislature passed Act 77, which authorized price ceilings for retail gasoline. At the time a study was conducted analyzing ceilings and these ceilings are slated to be imposed in October, 2005. Just such an intersection was revealed in the Fall of 1998 when the attorney general for Hawaii filed suit against the two refiners with operations in the state alleging collusion in gasoline markets. That Hawaii truly is an island market only serves to emphasize the possibility of market power in an industry with only two producers and high entry costs.

To estimate market power, it is common to compare price to marginal cost. Yet marginal cost in gasoline production is privately observed and closely guarded. As an alternative, wholesale gasoline prices (which are observed) can be compared across markets. In the absence of market power, wholesale prices in distinct markets should tend toward the same value. In the table below, we see that wholesale gasoline prices are remarkably high relative to spot markets in both Los Angeles and Singapore (the two markets in closest proximity to Hawaii). Moreover, the minimum price difference is quite large, indicating that the average price differences are not driven by several months with uncharacteristically high prices in Hawaii.

<table>
<thead>
<tr>
<th>Wholesale Gasoline Price Differences : Cents/Gallon</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992-2004 Mean Minimum</td>
</tr>
<tr>
<td>Hawaii - LA 33.8 -0.9</td>
</tr>
<tr>
<td>Hawaii - Singapore 44.0 19.0</td>
</tr>
</tbody>
</table>

Of course large wholesale price differences may only be evidence of the cost of shipping, unloading and transporting gasoline to retail outlets. In response to queries by the Hawaiian state government, Stillwater (2003) estimated the cost of performing these services. The estimated costs of delivery were 8 cents per gallon for gasoline from Singapore and 18 cents per gallon for gasoline from Los Angeles. The estimates lead to the remarkable finding that the wholesale gasoline price difference between Los Angeles and Hawaii exceeded import costs for more than a decade.

Disentangling the exercise of market power from the reactions of a competitive market to supply and demand shocks presents a challenge. As detailed in Borenstein et al. (2004), if refiners are producing near capacity, supply is inelastic with respect to price. Because consumption of gasoline is also price inelastic (over short horizons) unforeseen shocks to either supply or demand will likely create large price swings. Such
capacity bottlenecks typically occur in industries with high average capacity utilization, whereas capacity utilization for the Hawaiian refiners most often falls between 85 and 90 percent. An alternative measure of the likelihood of capacity constraints is the amount of storage capacity available. Hawaii is blessed with the storage to handle 28 days of gasoline demand, far greater than the US average of 13 days. With these facts at hand it is unlikely that capacity constraints are the explanation for high gasoline prices. This is borne out in Figure 1, which presents the graph of wholesale gasoline price differences between Hawaii and Singapore. While there is variation over time, there is little evidence of sharp spikes followed by a return to arbitrage levels (of less than 20 cents per gallon).

![Gasoline Wholesale Price Difference: Hawaii-Singapore](image)

In addition to gasoline, Hawaiian refiners produce jet fuel. The two (along with several minor products) are produced jointly from crude oil. As gasoline and jet fuel are companion goods, examination of jet fuel prices can shed light on the question of market power. Jet fuel is more volatile, and hence more expensive to transport, than gasoline. To the extent that price differences are driven by transit costs, jet fuel should have larger price differences. Yet, as the following table makes
clear, wholesale price differences for jet fuel are far lower than those for gasoline, with an average that is substantially less than the cost of importing jet fuel.

Hawaii - Singapore Wholesale Price Differences : Cents/Gallon  
1992-2004 Mean Minimum  
Jet Fuel 7.1 -6.7  
Gasoline 44.0 19.0

To see that average values are not misleading, we present graphs of gasoline and jet fuel wholesale price differences in Figure 2. One can quickly see that the different behavior of the two markets is sustained over time.

A second possible explanation, which captures the relative price differences in the two markets, is that gasoline is the principal product of refiners. Refiners set production levels for gasoline, with jet fuel as a residual product that is sold at a lower profit margin. Such an argument is hard to sustain in light of the low gasoline production levels: Hawaiian refineries devote 19 percent of their production to gasoline while the national average is 44 percent.
Although we do not have direct measures of marginal cost, indirect evidence is provided by the composition of output. For the two refiners (ChevronTexaco and Tesoro), Stillwater (2003) estimates the following composition as typical of each refinery

<table>
<thead>
<tr>
<th></th>
<th>ChevronTexaco</th>
<th>Tesoro</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gasoline</td>
<td>14,000</td>
<td>14,000</td>
</tr>
<tr>
<td>Jet Fuel</td>
<td>13,000</td>
<td>26,000</td>
</tr>
</tbody>
</table>

where all quantities are in barrels per day. In light of the fact that chemical laws restrict the substitution of gasoline for jet fuel in the production process, these production estimates are remarkable. It seems that Tesoro is refining far more crude oil (to produce the requisite jet fuel supply) but that the two refiners have evenly divided the gasoline market.

The following chart shows the time path of wholesale price differences presented earlier, with the timing of major events superimposed. The approval and opening of import terminals appears to have had little impact on price behavior. In contrast, the filing of the lawsuit seems almost coincident with a sustained decline in the wholesale price difference for gasoline.
Given that import terminals potentially add rivals to the existing refiners, why don’t the wholesale price differences react to the terminal openings? For the case of jet fuel, wholesale price differences are always less than the cost of transporting jet fuel between markets. As alluded to earlier, the HFFC import terminal is a foreign trade zone, created not in response to high jet fuel prices but to avoid taxes on fuel used for overseas flights. Indeed, the HFFC terminal receives jet fuel not only via ship but also through pipelines that are directly linked to each refinery.

The gasoline import terminal is not a foreign trade zone, as the tax advantages cannot be conferred on domestic consumption. Rather, the terminal is designed to offload ships, in direct competition with the two refineries. (When Chevron and Texaco merged in 2001, the court ruled that the new company could not control both a refinery and a share of the import terminal.) Despite this, the import terminal appears to have little impact on prices. To shed light on the issue, the following figure contains graphs of the quantity of jet fuel and gasoline passing through the import terminals. The jet fuel terminal has been an active conduit since its inception. In contrast, the gasoline terminal is virtually unused. Such behavior would be consistent with import terminal owners extracting price concessions from the refiners in response to an agreement not to import.
3 Economic Model

The analysis of Green and Porter (1984) is a natural starting point to model the market. In their work, Green and Porter study an industry with entry barriers that result in stable market shares for the producers. The key result is that occasional price wars, in the absence of new entry, may signal anticompetitive behavior. In equilibrium there are two regimes. In the first regime the producers reward each other (cooperate) with a tacit agreement to maintain high prices. In the second regime, which arises when a producer responds to an unexpected demand drop, a producer punishes other producers by forcing prices downward (thereby cutting the profits of all producers). After a suitable length of time passes, the “punishment” ends and prices (and profits) increase for all producers.

Given the posited behavior in the industry, a natural structure for analysis is to estimate a simultaneous equations model for the industry that switches according to the latent regime. To obtain supply functions, we modify the work of Porter (1983) to allow for production of more than one good. Each refiner faces a distinct cost function for the quantity of gasoline $Q$ and jet fuel $\tilde{Q}$ produced. For period $t$, the cost function of
The action of refiner \( i \) is

\[
C_i \left( Q_{it}, \tilde{Q}_{it} \right) = F_i + a_i Q_{it} \tilde{Q}_{it},
\]

where \( F_i \) captures fixed cost. The elasticities of variable cost with respect to output \((\gamma, \delta)\) must satisfy \( \delta + \gamma > 1 \) to ensure an equilibrium exists. The firm specific parameters \( F_i \) and \( a_i \) reflect the fact that technology varies over refiners.

Because the gasoline from each refiner is homogeneous (and so too is jet fuel), each refiner should charge the same price in equilibrium. As the jet fuel market is assumed to be competitive

\[
\tilde{P}_t = g_{MC_i} \left( Q_{it}, \tilde{Q}_{it} \right)
\]

where \( g_{MC_i} \) is the marginal cost of jet fuel production for refiner \( i \). The actions of refiners in the gasoline market are governed by

\[
P_t \left( 1 + \frac{\theta_{it}}{\alpha_1} \right) = MC_i \left( Q_{it}, \tilde{Q}_{it} \right)
\]

where \( MC_i \) is the marginal cost of gasoline production for refiner \( i \), \( \alpha_1 \) is the price elasticity of gasoline demand and \( \theta_{it} \) equals 0 if they act as Bertrand producers and equals 1 if they maximize joint profits. (If they produce at Cournot output levels, then \( \theta_{it} = s_{it} = \frac{Q_{it}}{\sum_i Q_{it}} \), the market share of firm \( i \).) Each supply equation will be log-linear with \( Q_{it} \) and \( \tilde{Q}_{it} \) appearing jointly as regressors.\(^1\)

Given the functional form assumptions, the market shares of each firm are invariant over time

\[
\tilde{s}_{it} = s_i = \frac{a_i^{1-(\delta + \gamma)}}{\sum_j a_j^{1-(\delta + \gamma)}} = s_i.
\]

As the only asymmetry among firms affects their production of each good equally, the market shares of each firm are the same in each product line.

\section{Econometrics}

The model outlined above suggests the following system of equations for the quantity and price of gasoline \((Q_t, P_t)\) and jet fuel \((\tilde{Q}_t, \tilde{P}_t)\). The supply equations are

\[
\ln P_t = \gamma_0 + D_M + \gamma_1 \ln Q_t + \gamma_2 \ln \tilde{Q}_t + \gamma_3 R_t + \gamma_4 \ln OPEC_t + \gamma_5 L_t + U_{St}
\]

\[
\ln \tilde{P}_t = \delta_0 + D_M + \delta_1 \ln \tilde{Q}_t + \delta_2 \ln Q_t + \delta_3 R_t + \delta_4 \ln OPEC_t + U_{\tilde{St}},
\]

\(^1\)As producers have market power, we refer to supply equations that hold for specific price and quantity pairs, rather than to supply functions that hold for arbitrary price and quantity pairs.
where $D_M$ is a collection of 11 monthly indicators, $OPEC$ is the OPEC price of oil, $R$ is a binary variable to indicate the regime (1 for cooperation) and $L$ is a binary variable indicating the timing of the lawsuit by the state attorney general. As these are supply equations, we expect that both $\gamma_1$ and $\delta_1$ should be positive, although theory does not indicate the sign of the cross quantity elasticity. Given the nature of oil as an input, it is natural to expect that $\gamma_4$ and $\delta_4$ are positive, as higher input prices likely lead to higher output prices. In response to the filing of the lawsuit, the refiners are likely to reduce the cost of gasoline (the lawsuit did not include the jet fuel market), hence $\gamma_5$ should be negative.

The fact the refiners respond to the lawsuit could in itself be evidence of collusion, but there may be strategic reasons for refiners to respond to the lawsuit even in the case of competitive markets. Most importantly for determination of market power, $\gamma_3$ should be positive reflecting the higher gasoline price in collusive regimes. The key identification of market power comes from the fact that $\delta_3$ should be insignificant, as no regimes are posited to exist for the jet fuel market. It is this distinction between markets that allows us to identify market power behavior from other factors that affect refiners.

The demand equations are

\[
\ln Q_t = \alpha_0 + \alpha_1 \ln P_t + \alpha_2 \ln I_t + \alpha_3 T M_t + U_{Dt} \\
\ln \hat{Q}_t = \beta_0 + \beta_1 \ln \hat{P}_t + \beta_2 \ln V_t + U_{\hat{D}t},
\]

where $I$ is personal income, $TM$ is a binary variable that takes the value 1 for the periods in which the import terminal is open, and $V$ is the number of visitors to Hawaii. As these are demand equations, we expect that both $\alpha_1$ and $\beta_1$ are negative. Conditional on all other demand factors, the opening of the gasoline import terminal should reduce the quantity of gasoline sold by the refiners ($\alpha_3$ negative). For jet fuel demand, $\beta_2$ should be positive as increasing the number of visitors naturally leads to greater demand for jet travel.

For the system there are five variables that are exogenous to the refiners control $X'_t = (\ln I_t, L_t, \ln OPEC_t, T M_t, \ln V_t)$. (While the monthly indicators are clearly exogenous, they appear in each equation and so play the role of the intercept.) Because there are no more than five slope coefficients in any one equation, the order condition for identification is satisfied. Further, as each of the equations is distinct from a linear combination involving any other equation, the rank condition for identification is satisfied.

In the above system it is clear that $Y'_t = \left(\ln Q_t, \ln \hat{Q}_t, \ln P_t, \ln \hat{P}_t\right)$ and $R_t$ are all endogenous. If the regime were observed, then the parameters
could be estimated via GMM (or 3SLS under conditional homoskedasticity). One could not use FIML, as we do not have an additional equation “for \( R_t \).” Because the regime is latent, we detail how to construct the likelihood. To do so, it is helpful to write the system as

\[
\Gamma Y_t + BX_t + DR_t = U_t,
\]

where the error vector \( U_t \) is independent through time with each vector drawn from the identical multivariate (of dimension four) Gaussian distribution with mean vector 0 and covariance matrix \( \Sigma \).

To determine the likelihood, we must specify a stochastic process for the latent regime variable. The simplest process is obtained by assuming, as does Porter (1983), that the latent regimes are independent through time and generated by identical distributions (iid), with

\[P (R_t = 1) = \lambda.\]

The resultant density for the observed data is

\[
f (Y_t | X_t; \theta) = (1 - \lambda) \left| 2\pi \Sigma \right|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\Gamma Y_t + BX_t)' \Sigma^{-1} (\Gamma Y_t + BX_t) \right\} + \lambda \left| 2\pi \Sigma \right|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\Gamma Y_t + BX_t + D)' \Sigma^{-1} (\Gamma Y_t + BX_t + D) \right\},
\]

where \( \theta = (\alpha, \beta, \gamma, \delta, \Sigma, \lambda) \). The log-likelihood function formed from this density is the incomplete data log-likelihood, which reinforces the fact that \( R_t \) is latent. The incomplete data log likelihood is

\[
L (\theta) = \sum_{t=1}^{n} \ln f (Y_t | X_t; \theta).
\]

The direct approach to obtain ML estimates is to construct the score for \( \theta \). Because the log density involves the logarithm of the sum of two components, optimization with the score is difficult.

Optimization would be far easier if the log density could be rewritten as the sum of two logarithm terms. The expectations-maximization (EM) algorithm gives a procedure to do just this. The algorithm begins with specification of the complete data log-likelihood (constructed under the fictional assumption that \( R_t \) is observed)

\[
L_C (\theta) = \sum_{t=1}^{n} \ln f_C (Y_t | X_t, R_t; \theta) + \sum_{t=1}^{n} \ln q_C (R_t; \lambda).
\]
If \( R_t = 1 \), then the component of the complete data log-likelihood corresponding to \( Y_t \) involves \( f_C (Y_t | X_t, R_t = 1; \theta) = |2\pi \Sigma|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} (\Gamma Y_t + BX_t + D)' \Sigma^{-1} (\Gamma Y_t + BX_t + D) \right\} \),

while the component for \( R_t \) involves \( q_C (R_t = 1 ; \lambda) = \lambda \). Because \( R_t \) is latent, the complete data log-likelihood cannot be constructed. Instead, we construct the optimal (with respect to quadratic loss) predictor of \( L_C (\theta) \), given the entire set of observed data \( \hat{L}_C (\theta) = E [L_C (\theta) | Y, X] \), which requires \( \hat{\eta}_t = P (R_t = 1 | Y, X) \).

The expectations step consists of construction of \( \{\hat{\eta}_t\}_{t=1}^n \) and then forming \( \hat{L}_C (\theta) \). To construct \( \hat{\eta}_t \) from the observed data, let \( \hat{\theta}^{(0)} \) be an initial estimator (the notation \( \hat{\theta} \) indicates that \( \hat{\theta} \) replaces \( \theta \)). Bayes rule yields

\[
\hat{\eta}_t = \lambda^{(0)} \frac{f (Y_t | X_t, R_t = 1; \hat{\theta}^{(0)})}{f (Y_t | X_t; \hat{\theta}^{(0)})}.
\]

The predictor of the complete data log-likelihood is then

\[
\hat{L}_C (\theta) = \sum_{t=1}^n \ln \hat{f}_C (Y_t | X_t, R_t; \theta) + \sum_{t=1}^n \ln \hat{q}_C (R_t; \lambda),
\]

where \( \ln \hat{f}_C = E [\ln f_C (Y_t | X_t, R_t; \theta) | Y, X] \) is

\[
(1 - \hat{\eta}_t) \ln f_C (Y_t | X_t, R_t = 0; \theta) + \hat{\eta}_t \ln f_C (Y_t | X_t, R_t = 1; \theta)
\]

and \( \ln \hat{q}_C = E [\ln q_C (R_t; \lambda) | Y, X] \) is

\[
(1 - \hat{\eta}_t) \ln (1 - \lambda) + \hat{\eta}_t \ln \lambda.
\]

The maximization step yields \( \hat{\theta}^{(1)} \) as the maximizer of \( n^{-1} \hat{L}_C (\theta) \). Because \( \ln f_C \) contains the sum of logarithm terms, the maximization step is much simpler to calculate than the score for the incomplete data log-likelihood.\(^2\)

The assumption that the regime variable is generated by an iid process does not accord with the structure delineated by Green and Porter. In particular, the punishment period they describe lasts for a fixed length of time, so the regime variable is not independent across

\(^2\)Kiefer (1978) establishes that the likelihood function has a bounded local maximum that is consistent and asymptotically normal, despite the possible presence of singularities.
time. In an effort to more adequately capture the concept of a punishment regime, we expand the model to include a transition matrix for \( R_t \). The transition matrix is

\[
\begin{array}{cccc}
R_{t-1} = 0 & R_t = 0 & \lambda_0 & 1 - \lambda_0 \\
R_{t-1} = 1 & R_t = 1 & 1 - \lambda_1 & \lambda_1
\end{array}
\]

with the unconditional probability again given by

\[
\lambda = \Pr (R_t = 1).
\]

For the Markov case, the incomplete data log-likelihood requires that we sum over all possible regime sample paths

\[
L (\theta) = \ln \left( \sum_{R_1 = 0}^{1} \cdots \sum_{R_n = 0}^{1} f (Y_1, \ldots, Y_n, R_1, \ldots, R_n | X_t; \theta) \right).
\]

Direct maximization is difficult, as the likelihood involves the log of the sum of many terms. The EM algorithm again provides a method of simplifying estimation. The complete data log-likelihood \( L_C (\theta) \) is as above with one slight change: If \( R_t = 1 \), then

\[
q_C = \lambda_1 + 1 - \lambda_0
\]

to reflect the fact that the preceding regime could be either 0 or 1. To construct \( \hat{L}_C (\theta) = E [L_C (\theta) | Y, X] \) we now require

\[
\hat{\eta}_t (j, k) = \Pr (R_t = k, R_{t-1} = j | Y, X).
\]

(The expectations step is detailed, and the recursions needed to construct \( \{\hat{\eta}_t (j, k)\}_{t=1}^{n} \) are contained in the appendix.)

With these calculated conditional probabilities, we form the expected completed data log-likelihood \( \hat{L}_C (\theta) \) as in (1). For observations 2 through \( n \), \( \ln f_C \) is

\[
[\hat{\eta}_t (0, 0) + \hat{\eta}_t (1, 0)] \ln f_C (Y_t | X_t, R_t = 0; \theta) + [\hat{\eta}_t (0, 1) + \hat{\eta}_t (1, 1)] \ln f_C (Y_t | X_t, R_t = 1; \theta)
\]

and \( \ln q_C \) is

\[
\hat{\eta}_t (0, 0) \ln \lambda_0 + \hat{\eta}_t (0, 1) \ln (1 - \lambda_0) + \hat{\eta}_t (1, 0) \ln (1 - \lambda_1) + \hat{\eta}_t (1, 1) \ln \lambda_1.
\]

For the first observation, the two components of \( \hat{L}_C (\theta) \) are

\[
\hat{\eta}_1 (0) \ln f_C (Y_1 | X_1, R_1 = 0; \theta) + \hat{\eta}_1 (1) \ln f_C (Y_1 | X_1, R_1 = 1; \theta)
\]

and

\[
\hat{\eta}_1 (0) \ln (1 - \lambda) + \hat{\eta}_1 (1) \ln \lambda,
\]

13
where $\hat{\eta}_t(0) = P(R_t = 0 | Y^n)$. For each observation $t$, it holds that $\hat{\eta}_t(0) + \hat{\eta}_t(1) = 1$. From this equality, one can deduce why there are four distinct values $\hat{\eta}_t(i, j)$ when there are only two distinct elements in the transition matrix. Because

$$\hat{\eta}_{t+1}(0, 0) + \hat{\eta}_{t+1}(0, 1) = \hat{\eta}_t(0),$$

this sum reflects the likelihood that observation $t$ is generated by regime 0. In contrast, the transition matrix elements $\lambda_0$ and $1 - \lambda_0$ condition on knowledge that observation $t$ is generated by regime 0, and so sum to one.

5 Results

We assembled data covering the period January 1992 to April 2004. Wholesale price and quantity data for gasoline and jet fuel come from the Energy Information Administration’s monthly bulletins. Prices for crude oil on the Singapore spot market (OPEC) come from a marketing survey, while income and visitor numbers are collected by the Hawaiian state government. We constructed indicator variables for the lawsuit and terminal openings from newspaper accounts and legal documents.

In the following table we present the coefficient estimates for the supply equations with standard errors in parentheses below the estimates. First, we estimate a positive partial impact of gasoline quantity on price (in keeping with a supply equation) but we are unable to precisely measure the corresponding relation in the jet fuel market. We also find a positive price elasticity with respect to the OPEC cost of oil. Moreover, jet fuel prices respond much more to the OPEC cost than do gasoline prices, which could be evidence of collusion in gasoline markets. To this end, it also appears that gasoline prices were lowered in response to the filing of the lawsuit by the state attorney general. Far stronger evidence is provided by the estimates of the regime coefficient. We find that, after conditioning on other factors affecting gasoline demand, periods in which the regime variable is 1 have significantly higher gasoline prices but no substantive change in jet fuel prices. As such, the regimes may indeed be capturing periods of collusion as they are capturing a force that is distinctly at work only in the gasoline market.

Estimates of Supply Equations
In the next table we present the coefficient estimates for the demand system. We find a negative partial impact of fuel price on quantity (in keeping with a demand equation). In addition, the predicted quantity demanded is strongly linked to the arrival of visitors (in jet fuel) although we are not able to precisely measure the impact of personal income on gasoline demand. Perhaps most interestingly, the opening of the gasoline terminal appears to have slightly increased the amount of gasoline sold by refiners.

<table>
<thead>
<tr>
<th>Regime</th>
<th>Gasoline</th>
<th>Jet Fuel</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln OPEC</td>
<td>.37</td>
<td>.62</td>
</tr>
<tr>
<td>Lawsuit</td>
<td>−.06</td>
<td>(−.11)</td>
</tr>
<tr>
<td>ln Q</td>
<td>2.37</td>
<td>−.39</td>
</tr>
<tr>
<td>ln ˜Q</td>
<td>−.73</td>
<td>.19</td>
</tr>
</tbody>
</table>

The transition matrix estimates shed further light on the nature of latent regimes. We find

\[ P(R_{t+1} = \text{Cooperate} | R_t = \text{Cooperate}) = .95 \]
\[ P(R_{t+1} = \text{Punish} | R_t = \text{Punish}) = .83 \]

Cooperative regimes have an expected length of slightly more than 2 years ((.05\(^{-1}\)) = 20 months). Punishment regimes are far shorter, lasting on average only 6 months ((.17\(^{-1}\)) = 6).

6 Conclusion

The evidence presented above may reveal collusive behavior on the part of refiners in Hawaii. The Hawaiian state government is currently considering price ceilings on retail gasoline. Yet these may simply serve
as a focal point of collusion. Knittel and Stango (2003) show how the imposition of ceilings on credit card interest rates served to raise average rates. Over time, states have dismantled the ceilings and average rates have fallen. Perhaps a better solution would be the open auction of terminal facilities.
Appendix

Ergodic Probabilities

Let $\Lambda$ be the transition matrix. Standard analysis of Markov processes yields the ergodic probabilities as the last column of $(A'A)^{-1}A'$, where $A = I_2 - \Lambda'$ (I_2 is the identity matrix of dimension 2 and 1_2 is the row vector containing the number 1 in each element).

Recursions for $\{\eta_t (j, k)\}_{t=1}^n$

The recursions detailed here are well known in the Hidden Markov Model literature (for example: Buckle, Haugh and Thomson (2004)). We first detail how to construct the conditional density $f(Y_t|Y^{t-1})$ where $Y^{t-1} = (Y_1, \ldots, Y_{t-1})$. (We suppress conditioning on $X$ throughout.) For the first observation we have only the unconditional density

$$f(Y_1) = (1 - \lambda)f(Y_1|R_1 = 0) + \lambda f(Y_1|R_1 = 1).$$

For the succeeding observation,

$$f(Y_2|Y^t) = \sum_{k=0}^1 [f(Y_2|R_2 = k, Y^t) P(R_2 = k|Y^t)].$$

Let $\kappa_t$ denote $f(Y_t|Y^{t-1})$ (with $\kappa_1 = f(Y_1)$), so the conditional density recursion is

$$\kappa_t = \sum_{k=0}^1 \left[ f(Y_t|R_t = k, Y^{t-1}) \sum_{j=0}^1 P_{jk} P(R_{t-1} = j|Y^{t-1}) \right],$$

where $P_{jk}$ is element $(j, k)$ of the transition matrix. (In fact, $f(Y_t|R_t = k, Y^{t-1})$ is simply $f(Y_t|R_t = k)$, as the simultaneous system does not contain lagged values of $Y_t$.)

Although $\kappa_{t-1}$ does not appear on the right side of the above equation, the presence of the filtered regime probability, $P(R_{t-1} = j|Y^{t-1})$, yields the recursive structure. To construct the filtered regime probability for observation one, Bayes rule implies

$$P(R_1 = 1|Y^1) = \frac{\lambda f(Y_1|R_1 = 1)}{f(Y_1)}.$$

For the remaining observations, the filtered regime probabilities are

$$P(R_t = k|Y^t) = \frac{f(Y_t|R_t = k, Y^{t-1}) P(R_t = k|Y^{t-1})}{f(Y_t|Y^{t-1})}.$$
If we let \( \alpha_t (k) \) denote \( P (R_t = k | Y^t) \), then the filtered regime probability recursion is

\[
\alpha_t (k) = \frac{f (Y_t | R_t = k, Y^{t-1})}{\kappa_t} \sum_{j=0}^{1} P_{jk} \alpha_{t-1} (j).
\]

To determine the smoothed regime probability, \( P (R_t = k | Y^n) \), we need an additional quantity. Let \( \eta_t (k) \) denote this smoothed regime probability, so

\[
\eta_t (k) = \frac{f (Y^n, R_t = k)}{f (Y^n)}.
\]

By the laws of conditional probability

\[
\frac{f (Y^n, R_t = k)}{f (Y^n)} = \frac{f (Y_{t+1}, \ldots, Y_n, R_t = k | Y^t) f (Y^t)}{f (Y^n)} = \frac{f (Y_{t+1}, \ldots, Y_n | Y^t, R_t = k) P (R_t = k | Y^t) f (Y^t)}{f (Y^n)}.
\]

Let \( \rho_t (k) = \frac{f (Y_{t+1}, \ldots, Y_n | Y^t, R_t = k) f (Y^t)}{f (Y^n)} \), so the smoothed and filtered regime probabilities are related as

\[
\eta_t (k) = \rho_t (k) \alpha_t (k).
\]

For observation \( n \), the smoothed and filtered regime probabilities are identical, so \( \rho_n = 1 \).

To determine the recursion for other values of \( t \), we first note that the ratio \( \frac{f (Y^n)}{f (Y^{n-1})} \) equals a recursive product of the conditional densities. In detail, for observation \( n-1 \), the definition of conditional probability implies \( \frac{f (Y^n)}{f (Y^{n-1})} = \kappa_n \). In consequence, \( \frac{f (Y^n)}{f (Y^n)} = \prod_{j=t+1}^{n} \kappa_j \). We next note that the conditional distribution of future observations satisfies a recursion that runs backward in time. For observation \( n-1 \),

\[
f (Y_n | Y^{n-1}, R_{n-1} = k) = \sum_{j=0}^{1} f (Y_n | Y^{n-1}, R_n = j) P_{kj}.
\]

For observation \( n-2 \),

\[
f (Y_{n-1}, Y_n | Y^{n-2}, R_{n-2} = k) = \sum_{j=0}^{1} f (Y_{n-1}, Y_n | Y^{n-2}, R_{n-1} = j) P_{kj}
\]

\[
= \sum_{j=0}^{1} f (Y_n | Y^{n-1}, R_{n-1} = j) f (Y_{n-1} | Y^{n-2}, R_{n-1} = j) P_{kj}.
\]
We combine the two facts noted to yield
\[
\rho_{n-2}(k) = \frac{\sum_{j=0}^{k} f(Y_n|Y^{n-1}, R_{n-1} = j) f(Y_{n-1}|Y^{n-2}, R_{n-1} = j) P_{kj}}{\kappa_{n-1} \kappa_{n}}
\]
\[
= \frac{\sum_{j=0}^{k} \rho_{n-1}(j) f(Y_{n-1}|Y^{n-2}, R_{n-1} = j) P_{kj}}{\kappa_{n-1}}.
\]
For the remaining observations, we simply replace \( n - 2 \) with \( t \).

Finally, we need the smoothed regime probabilities
\[
\eta_t(j, k) = P(R_t = k, R_{t-1} = j|Y^n).
\]

By the laws of conditional probability
\[
\eta_t(j, k) = \frac{f(Y_t, \ldots, Y_n|Y^{t-1}, R_t = k) P_{jk} P(R_{t-1} = j|Y^{t-1}) f(Y^{t-1})}{f(Y^n)}
\]
\[
= \frac{f(Y_t|Y^{t-1}, R_t = k) f(Y_{t+1}, \ldots, Y_n|Y^{t-1}, R_t = k) P_{jk} \alpha_{t-1}(j) f(Y^{t-1})}{f(Y^n)}
\]
\[
= f(Y_t|Y^{t-1}, R_t = k) \frac{\rho_t(k) P_{jk} \alpha_{t-1}(j)}{\kappa_t}.
\]
References


