Collusion in the Austro-Hungarian Sugar Industry 1889-1914

PhD Research Seminar in Microeconomics

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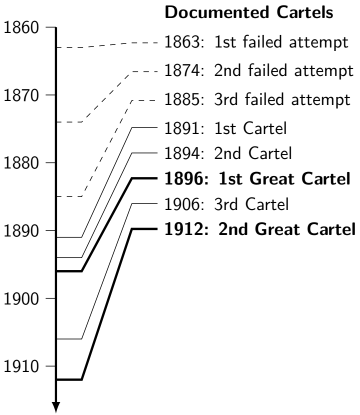
Research Question

- We study the success and failure of several cartels in historical Austria-Hungary's sugar industry
- Cartel dates are documented, we aim to find and compare the achieved degree of collusion
- To measure the degree of collusion we estimate a *conduct parameter* Formula



Motivation

- Sugar industry accounted for X% of monarchy's GDP and X% exports
- Estimating cartel success lets us understand the impact of a monitoring device
- Also sheds light on role of government which helped implement monitoring device
- Can refine methodology for estimation of dynamic demand

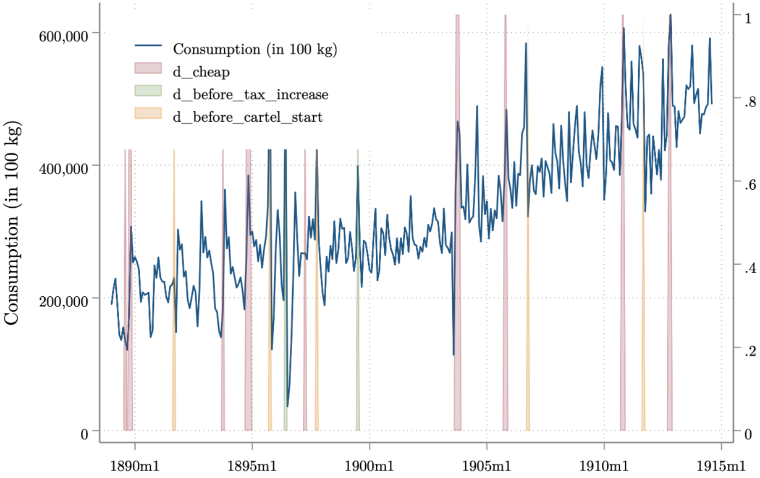
Plan

- Estimating conduct requires demand and supply estimation Formula
  - model how consumers make purchase decisions
  - model how firms compete (equilibrium FOC)
- Today's focus: demand side
- Challenges
  - storeable product $\rightarrow$ use a dynamic model of demand
  - consumer heterogeneity $\rightarrow$ allow for heterogeneity in taste and storage
  - non-linear model $\rightarrow$ cannot use OLS
  - only have montly aggregate data $\rightarrow$ use a method with low data requirements
  - hard to evaluate moment conditions $\rightarrow$ use simulation for estimation
  - prices are endogenous $\rightarrow$ use instruments: tax changes, cartel dates
- Next steps: supply and eventually conduct estimation

Dynamic Demand

- Large share of IO literature is based on static models of demand
- Credible for goods that perish quickly
- But sugar is a storeable product
- We find suggestive evidence for stockpiling

Hints of stockpiling



- when future price increases become public, a month later demand peaks

Hints of stockpiling

Table 1—Quantity of Two-Liter Bottles of Coke Sold

	$S_{t-1} = 0$	$S_{t-1} = 1$	
$S_t = 0$	247.8	199.4	227.0
$S_t = 1$	763.4	531.9	622.6
	465.0	398.9	

Notes: The table presents the average across 52 weeks and 729 stores of the number of two-liter bottles of Coke sold during each week. As motivated in the text, a sale is defined as any price below one dollar.

Preview

- (Expected) Preliminary Results:
  - we find that storing matters
  - dynamic models performs significantly better (differently) than static model
  - an approach used in the literature is inconsistent, but we can correct it by resorting to the *methods of simulated moments*

Literature

- **Narrative evidence on cartels in the sugar industry.** Fink (2016), Genesove and Mullin (1997). $\rightarrow$ *We add quantitative evidence*
- **Dynamic demand estimation.** Hendel and Nevo (2013), Perrone (2017), Hendel and Nevo (2006) $\rightarrow$ *We add an application that addresses endogeneity in prices*
- **Conduct parameter identification.** Bresnahan (1982), Porter (1983), Genesove and Mullin (1998),
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- **Conduct parameter extensions.** Salvo (2010)

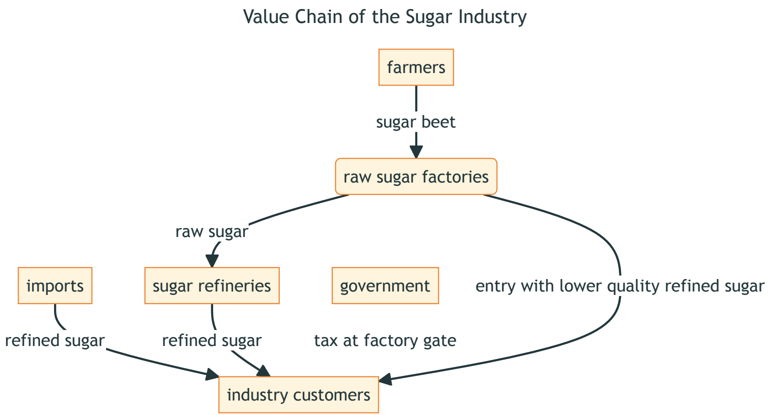
Product Market

- We focus on refined sugar
- and treat it as a homogenous product (like Genesove and Mullin (1998))
- Different types exist, but either very substitutable or not substitutable at all

Geographical Market

- K & K Monarchy map here?
- No imports, but possibility of import constraint

Value Chain of the Sugar Industry



Data Sources

Wochenzeitschrift

- monthly prices
- monthly quantities
-
-

Fink (2016)

- Taxes
- Cartel Periods
-
-

Source?

- Income
- GDP
- Population
- CPI

Demand Model

- We borrow the model from Hendel and Nevo (2013) and make the following assumptions:

1. Two types of consumers: storers and non-storers
    - They have potentially different quasi-linear utility functions
    - can change over time through demand shocks
    - expenses for sugar are small relative to wealth, so we can abstract from income effects

- The importance of storing consumers is scaled by a relative intercept parameter
    - ω consumers who do not store
    - $(1-\omega)$ consumers who store when storage is optimal
    - with $\omega = 1$ demand is static

Demand Model

2. Simple storage technology:
   - can store for free for T periods
   - purchases perish after T periods
3. Future demand needs (including shocks $\varepsilon_{t+\tau}$) are known $\tau = 0, 1, ..., T$ Periods ahead
4. For now: perfect foresight of prices

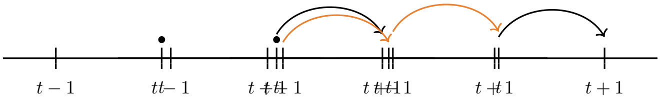
Notion of "Sales Period"

- **Definition.** A product is *at sale* in period t if $p_t \leq p_{t+1}$
- Iterating backward: a product *was* at sale in period $t-1$ if $p_{t-1} \leq p_t$
- with perfect foresight consumer knows
  - p_{t+1} in period t
  - p_t in period $t-1$
- Idea: a sales period is one when it is optimal for the storing consumers to store
- for $T = 1$ that is the case when price today is lower than price tomorrow, so consumers anticipate the price increase and buy for storage

State Space

- In a given period t a product is at sale or not $\{S, N\}$
- If consumers only store for 1 period $(T = 1)$ it suffices to look at yesterday $t - 1$ and today t, i.e., $\mathcal{S} = \{(s_{t-1}, s_t)\}$
- This gives four states of the world $\{S, N\}^2 = \{(N, N), (S, N), (N, S), (S, S)\}$
- For example state (S, N) means that there was a sale at $t - 1$, but no sale at t

What does a storing consumer buy today? $(T = 1)$



(a) NN (b) NS (c) SN (d) SS

Identification strategy

$$X_t^s(p_{t-1}, p_t, p_{t+1}) = \begin{cases} Q_t^s(p_t) & \text{NN} \\ Q_t^s(p_t) + Q_{t+1}^s(p_t) & \text{NS} \\ 0 & \text{SN} \\ Q_{t+1}^s(p_t) & \text{SS} \end{cases}$$

- Given this structure, we can exploit the variation in prices and states to identify storer's and non-storer's demand parameters.

Functional Form

- We assume demand for refined sugar to be linear in logs, that is:

$$\log q^{h}_{t,\text{buy for } t+\tau} = \log(\omega^{h})\alpha - \beta^{h} p_t + \varepsilon_{t+\tau}$$

- $h = s, n$ ... storers and non-storers
- log ω^h is the ~~fraction~~ multiplier of consumers demand to intercept α when all prices are 0
- τ indicates if a consumer buys for future periods ($\tau = 0$ for non-storers)
- We specify $\varepsilon_t \overset{iid}{\sim} ??$ IN BLP THIS IS RANDOMNESS IN CHOICE, taste heterogeneity
- This implies that the elasticity of demand is not constant but changes with the price level

Purchases can include future demand

- A non-storing consumer only considers buying for today

$$X_t^n = q_t^n = \omega e^{\alpha - \beta^n p_t + \varepsilon_t}$$

- A storing consumer knows demand shocks T periods ahead, and considers buying today for consumption in future periods

$$X_t^s = (1-\omega)[\mathbb{1}_{\text{buy for t}}\ e^{\alpha - \beta^s p_t + \varepsilon_t} + \mathbb{1}_{\text{buy for t+1}}\ e^{\alpha - \beta^s p_t + \varepsilon_{t+1}}]$$

- Aggregate demand

$$Q_t = X_t^n + X_t^s = \omega e^{\alpha - \beta^n p_t + \varepsilon_t} + (1-\omega)[\mathbb{1}_{\text{buy for t}}\ e^{\alpha - \beta^s p_t + \varepsilon_t} + \mathbb{1}_{\text{buy for t+1}}\ e^{\alpha - \beta^s p_t + \varepsilon_{t+1}}]$$

Estimating Equation

Rearranging to isolate constant α

$$Q_t = \underbrace{(\omega e^{-\beta^n p_t + \varepsilon_t} + (1-\omega)[\mathbb{1}_{\text{buy for t}}\, e^{-\beta^s p_t + \varepsilon_t} + \mathbb{1}_{\text{buy for t+1}}\, e^{-\beta^s p_t + \varepsilon_{t+1}}])}_{=:\tilde{Q}_t} \quad e^{\alpha}$$

Taking logs

$\log Q_t = \log(\tilde{Q}_t e^{\alpha}) = \log(\tilde{Q}_t) + \alpha$

Note that we can remove α by demeaning $\log Q_t$

Specifying an additive econometric error term we arrive at the estimating equation

$$\log X_t = \alpha + \log \tilde{Q} + u_t$$

Where the aggregation over both consumer types (and state dependence) makes the

The issue with Hendel and Nevo (2013)

- Hendel and Nevo (2013) use NLLS and assume $E(u_t|P_{t-1}, P_t, P_{t+1}) = 0$ – we argue that this is not true and already $E(u_t) \neq 0$
-
- Cast as equivalent GMM makes it easier to see what this implies
- **GMM set up:** $\mathbb{R}^n$ be the space of data. $\mathbb{P} \subset \mathbb{R}^k$ parameter space. The *Global identification condition* requires to find $\beta_{(k\times 1)} \in \mathbb{P}$, where we have $\mathbf{f} : \mathbb{P} \times \mathbb{R}^n \to \mathbb{R}^r$, such that

$$\mathbb{E}[\mathbf{f}(\mathbf{x}, \beta)]|_{\beta=\beta_0} = \mathbf{0},$$

if and only if β_0 is the true parameter.

- The equivalent moment condition is $\mathrm{E}\left[\nabla_\beta g\left(x_t, \beta\right) \cdot \left(y_t - g\left(x_t, \beta\right)\right)\right] = 0$

The issue with Hendel and Nevo (2013)

- Essentially, if demand shocks are iid, e.g., $\varepsilon_t \overset{\text{iid}}{\sim} N(0,1)$

$$E(\varepsilon_t + \varepsilon_{t+1}) = 0 E(ln(e^{\varepsilon_t + \varepsilon_{t+1}})) = 0 \text{But:} \quad E(ln(e^{\varepsilon_t} + e^{\varepsilon_{t+1}})) \neq 0 \text{which implies that in Hende}$$

- That is their NLLS estimator is inconsistent and the distortion depends on the standard deviation of the demand shocks
- To doublecheck we conducted a Monte Carlo Simulation and do not find that the distortion fades away as sample size increases

Simulation of Hendel and Nevo (2013)

- We assume $\varepsilon_t \overset{\text{iid}}{\sim} N(0,1)$ and [insert price distribution]
- especially omega is biased [try simulation without demand shocks!]
- put graph here with 4 panels

Identification

Want to identify ω, β^n, β^s (α not necessarily)

key: 4 states, give 4 different prediced purchases

moment conditions do not need to have same sample!

get a moment condition for every of the 4 statesß

Unconditional Moment Conditions

$$E[\hat{u}] = 0E[\hat{u}] = \int\int\int (\log Q_t - \log Q_t(\widehat{X_t, \varepsilon_t}, \varepsilon_{t+1}, \theta)) d \Pr(\varepsilon_t)\ d \Pr(\varepsilon_{t+1})\ d \Pr(Q_t, X_t)$$

- Challenge: We do not observe $(\varepsilon_t, \varepsilon_{t+1})$, but also cannot numerically evaluate inner double integral
-

Endogeneity of Prices

- Cannot use moments like $E(u_t p_t)$, $E(u_t p_{t-1})$, $E(u_t p_{t+1})$ as prices are endogenous
- Firms are likely to supply more in times of high current prices
- Past (and future) prices are also endogenous as they influence the current state
- Want to find exogenous instruments that satisfy $E(u_t | z_{t-1}, z_t, z_{t+1}) = 0$,
- And then use GMM setting moments conditions like $E(u_t)$, $E(u_t z_t)$, \$E(u_tz_{t-1}), \$$E(u_t z_{t+1})$ equal to zero

Method of Simulated Moments

Following Pakes and Pollard (1989) we replace the intractable function with a random function generated from a simulation sample s times as large as the original data sample.

The algorithm is

1. Draw s random vectors of ε_t
2. Fix a candidate parameter vector θ_0
3. Calculate the simulation analogue of the moment conditions, e.g., $\hat{h}(x,\theta) = \frac{1}{s}\sum \log Q_t - \log Q_t(\widehat{x, \varepsilon_t,} \varepsilon_{t+1}, \theta_0)$
4. iterate over 2. and 3. to find the θ^* that pushes the sample analogs of the moment conditions based on their simulation analog as close to 0 as possible

Results – static

OLS, IV

Table OLS, IV, robustness checks with e.g. excluding stockpiling outliers and periods

Results – dynamic

GMM

table Table best OLS, best IV, GMM dynamic model

Summary

- sugar is a storeable product
- a simple model of demand that accounts for a storage decision improves estimates
- a method for aggregate data from the literature is biased but can be corrected with simulated method of moments

Work in Progress

- Want to estimate conduct parameter θ, but only prices are observed

$$\theta = \eta(P)\frac{P-c}{P} \equiv L_\eta$$

Need to

  - estimate elasticity of demand η $\rightarrow$ Demand Estimation ($\checkmark$)
  - estimate price-cost margin (and back out marginal cost c) $\rightarrow$ Supply Estimation ($\rightarrow$ next)
  - identify conduct parameter and test H0: $\theta = 0$ ($\rightarrow$ next)

- Supply and thus Conduct estimation may benefit from taking into account constraints from imports as in Salvo (2010)

Summary

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Appendix

Summary Statistics

table mean, sd, etc

- price
- quantity
- sales period dummy

Estimating Equation by state

$E(u|P_t, P_{t-1}, P_{t+1})$ what if support of P is only two prices?

$$(\omega e^{-\beta^n p_t + \varepsilon_t} + (1-\omega)e^{-\beta^s p_t + \varepsilon_t})$$ (NN - easy)

$$(\omega e^{-\beta^n p_t + \varepsilon_t} + (1-\omega)[e^{-\beta^s p_t + \varepsilon_t} + e^{-\beta^s p_t + \varepsilon_{t+1}}])$$ (NS - hard)

$$(\omega e^{-\beta^n p_t + \varepsilon_t})$$ (SN - probably hard)

$$(\omega e^{-\beta^n p_t + \varepsilon_t} + (1-\omega)e^{-\beta^s p_t + \varepsilon_{t+1}})$$ (SN - easy)

- Assume aggregate demand is a function of "conduct" θ_j, $Q(\theta)$
- Then in a static one-shot Cournot game, equilibrium is characterised by firms' best response, i.e., the optimal pricing condition:

$$\text{FOC:} \quad P(Q) + P'(Q)\theta_j q_j = MC_j(q_j)$$

- Deviations from this game can be modelled by scaling with a conduct parameter θ, which is

$$\theta = \eta(P)\frac{P-c}{P} \equiv L_\eta$$

Three interpretations of θ or ϕ

Identification of Conduct

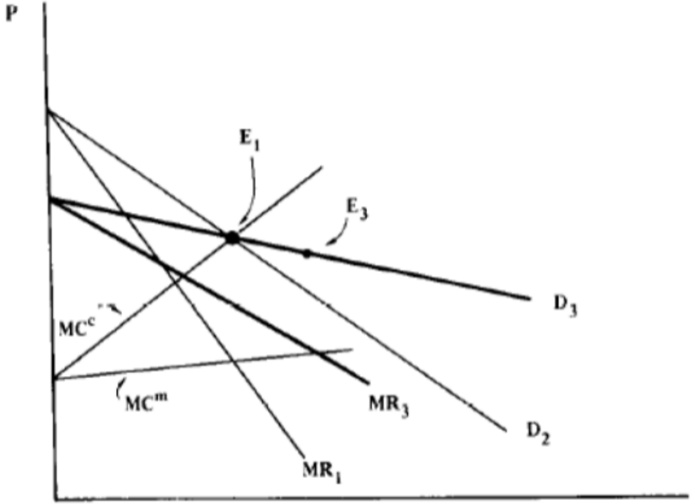
Goal: identify conduct separately from (slope of) marginal cost

Four strategies:

- assume constant marginal cost $MC(q) = c$
- construct marginal cost estimates and plug them in
- have a good demand rotator, that does not change marginal cost parameters and optimally also not shift demand
- focus on changes in conduct or assume that firms competete perfectly outside of cartel periods

A famous graph

Bresnahan (1982)



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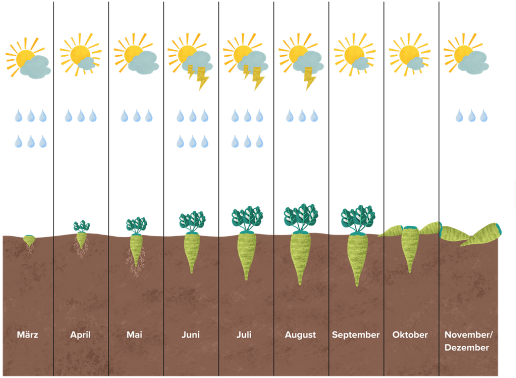
März
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