Collusion in the Austro-Hungarian Sugar Industry 1889-1914

PhD Research Seminar in Microeconomics

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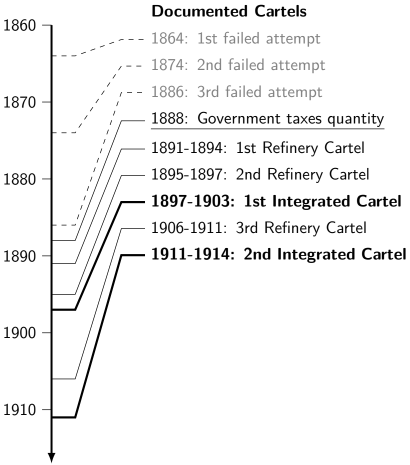
Research Question

- We study the success and failure of several cartels in historical Austria-Hungary's sugar industry



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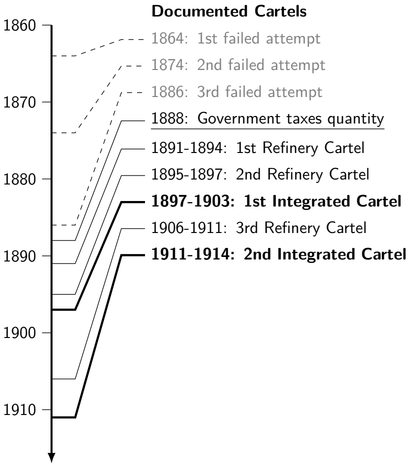

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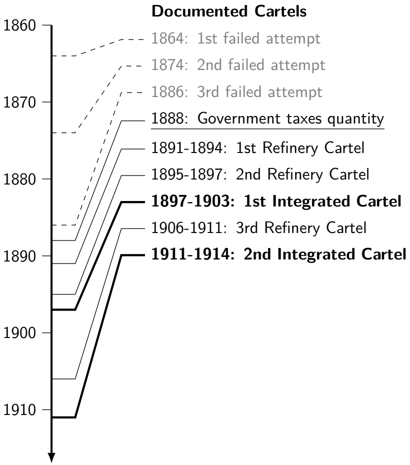

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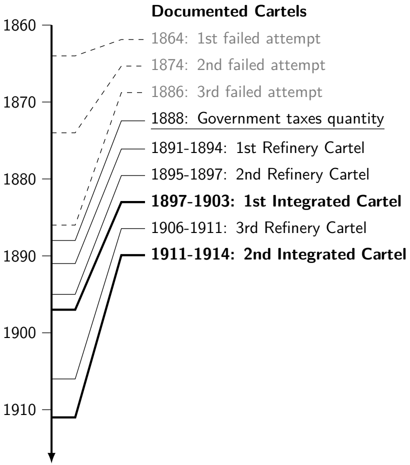
- To measure the degree of collusion we estimate a *conduct parameter* Details



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- Comparing achieved collusion lets us compare integrated with downstream cartels
- Contemporary sugar cartel cases: KR 2007, AUT 2010, GER 2014
- Refine methodology used in the empirical IO literature

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- Next steps: supply and eventually conduct estimation

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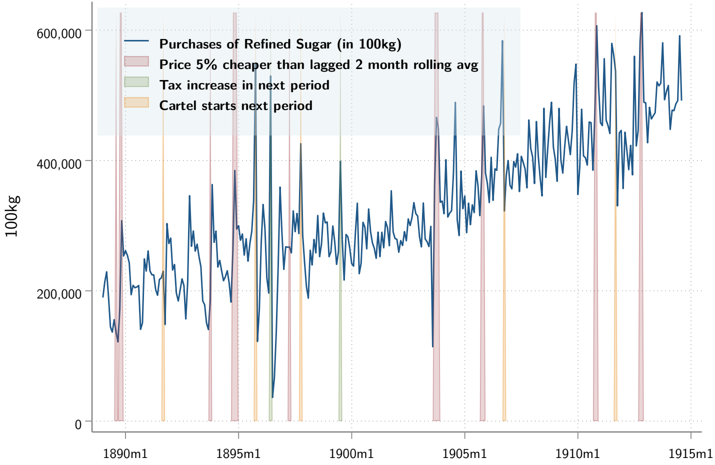
- Sugar is a storable product
- Suggestive evidence that consumers stockpiled before known price increases

Hints of stockpiling

- Demand peaks 1 month before price increases



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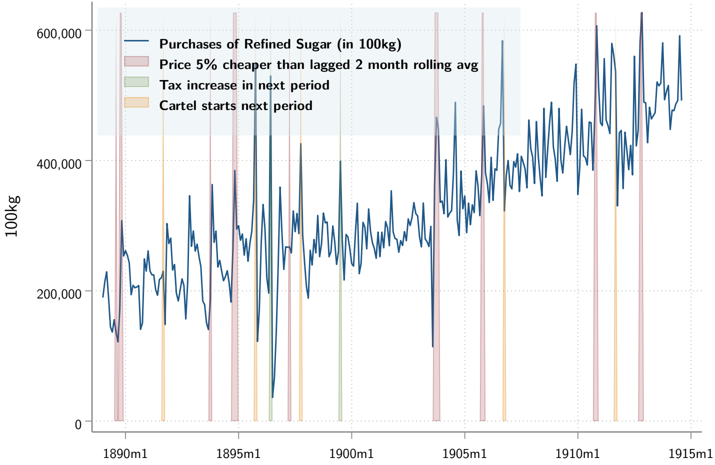

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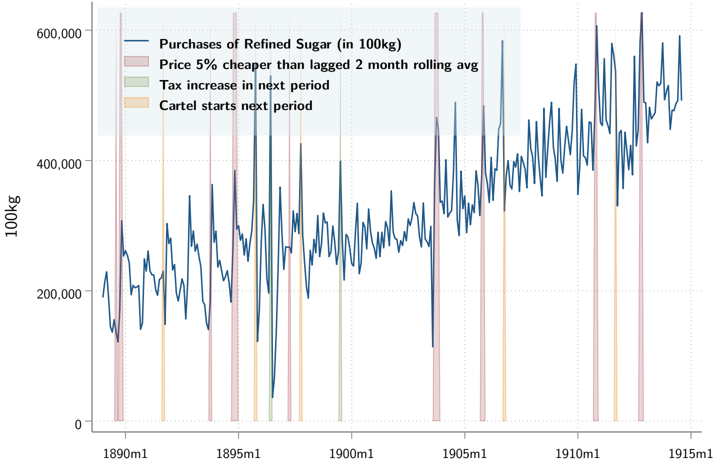
- There is actual historical evidence of stockpiling



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  - Prices are endogenous $\rightarrow$ need instruments: tax changes, cartel dates

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  - An estimator based on a dynamic model used in the literature looks inconsistent
  - A *Method of Simulated Moments* estimator is a feasible alternative

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- **Testing firm conduct**. Nevo (1998), Miller and Weinberg (2017), Magnolfi and Sullivan (2022), Duarte et al. (2023)

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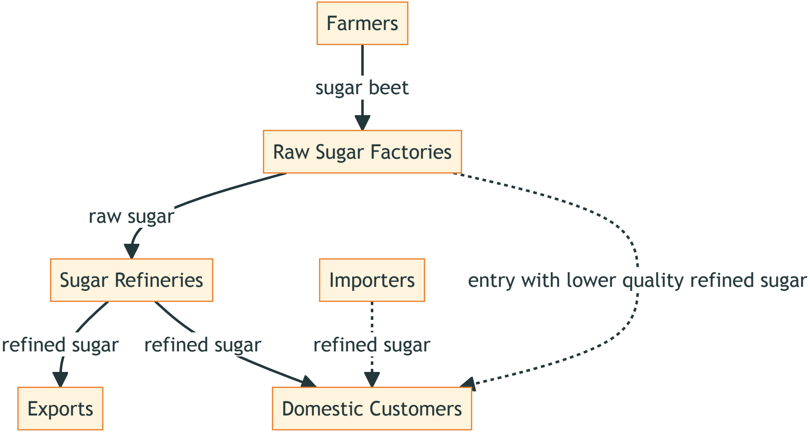
Value Chain of the Sugar Industry



Geographical Market (demand side)

- We consider the monarchy as a single market
- Transport cost small fraction of price
- Limited competition between Cis- and Transleithania
- No imports but suggestive evidence of import constraint as in Salvo (2010)

Source: Schober (1906)

Data Sources

Centralverein

- monthly prices
- monthly quantities
- monthly Ex/Im
- transport cost (ballpark)

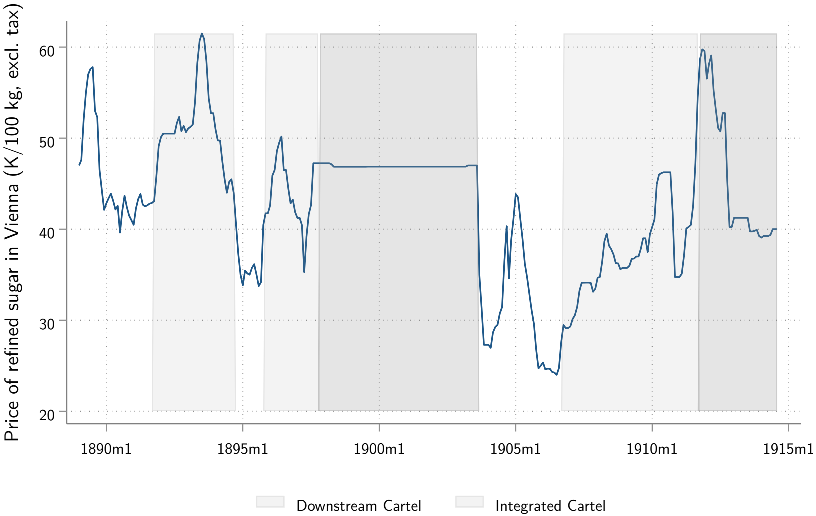
K. & K. Ministries

- sugar taxes
- import tariff
- export subsidy

Various

- pop: Schulze (2000)
- GDP: Schulze (2000)
- CPI: Mühlpeck et al. (1979)
- cartel periods: various

Prices (excl. tax)



Summary Statistics

Table 1: Summary Statistics

Variable	Mean	SD	Min	Max
Quantity X_t	328,250	110,218	36,294	627,049
Price P_t	74.57	8.53	55.75	97.75
Sales Period S_t	0.08	0.27	0.00	1.00

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- **A1.** Two types of consumers: storers and non-storers
  - They have potentially different quasi-linear (concave) utility functions
  - Which change over time through demand shocks
  - Expenses for sugar small relative to wealth, so can abstract from income effects

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- **A4.** For now: perfect foresight of prices (rational expectations possible)

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- Definition can be generalised for $T > 1$ (with $p_t = p_t^{ef} := \min\{p_{t-T}, ..., p_t\}$)

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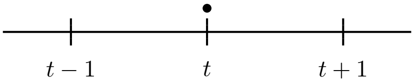
- E.g., state (C, N) means that there was a sale at $t-1$, but no sale at t

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



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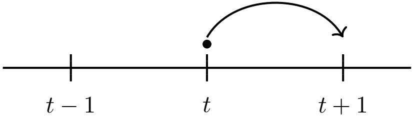

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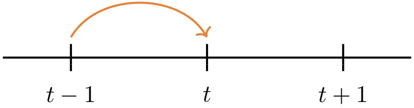

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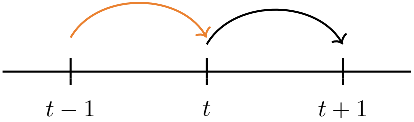

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Purchasing Patterns

- Storers' purchases X_t^s vary by state

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

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- Identification for non-storers is standard (only price variation)

Hints of State Dependence

Table 2: Quantity of Refined Sugar Sold

	$C_{t-1} = 0$	$C_{t-1} = 1$	
$C_t = 0$	324,906	287,129	322,777
$C_t = 1$	363,274	452,483	393,011
	327,067	342,247	328,250

Notes: The table presents the average across all months of the 26 years from 1889-1914. The unit is 100kg.

Functional Form

- Log-linear *demand needs* in period $t + \tau$ when purchases in period t Implied Elasticity

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- $\tau = 1$ marks purchases of storers for future periods ($\tau = 0$ for non-storers always)
- Consumers know the demand shock $\varepsilon_{t+\tau}$ with general distribution $F(\varepsilon_t)$

Purchases can include future demand

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- A storing consumer knows tomorrow's demand shock today, and considers buying today for consumption in future periods

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

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- Aggregate demand in period t

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

Estimating Equation

- Rearranging to isolate constant α

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

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- Rearranging to isolate constant α

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- Because of aggregation over types (and state dependence) the parameters enter in a non-linear way

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- Non-additively separable shocks are not subsumed by an additive error term u_t

Non-additively separable shocks

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

$$E(\varepsilon_t + \varepsilon_{t+1}) = 0$$

$$E(\ln(e^{\varepsilon_t + \varepsilon_{t+1}})) = 0$$

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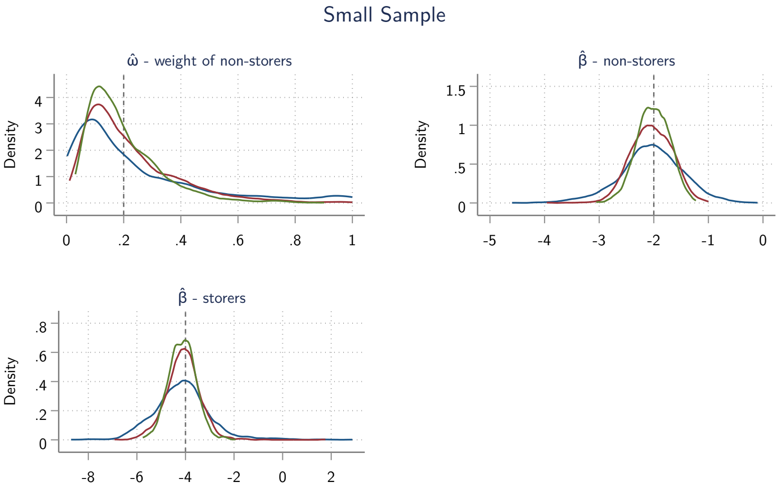
- If they estimate a different model, it is not clear why their NLLS estimator should be consistent for the actual model
- Thus we examine the sampling distribution of $\hat{\theta}^{H\&N(2013)}$ in a Monte Carlo simulation

Simulation Set Up

- Attempt to replicate setting of Hendel and Nevo (2013)
    - Similar mean and sd of price, quantity, sales periods and sales definition
    - Set true parameters approx. equal to their estimates
    - $P_t \overset{\text{iid}}{\sim}$ mixture of truncated $L(0.95, 0.1), L(1.25, 0.1)$ Histogram
- Differences
    - Can only assume demand shocks, and use $\varepsilon_t \overset{\text{iid}}{\sim}$ truncated $N(0, 1)$
    - Time series rather than panel
    - Homogenous product rather than differentiated products
- Identification arguments rely on time series variation, so method should work
- We initialise the NLLS estimation routine with the true θ

Simulation of Hendel and Nevo (2013)



Repetitions = 1000
Sample Sizes: 100, 200, 300

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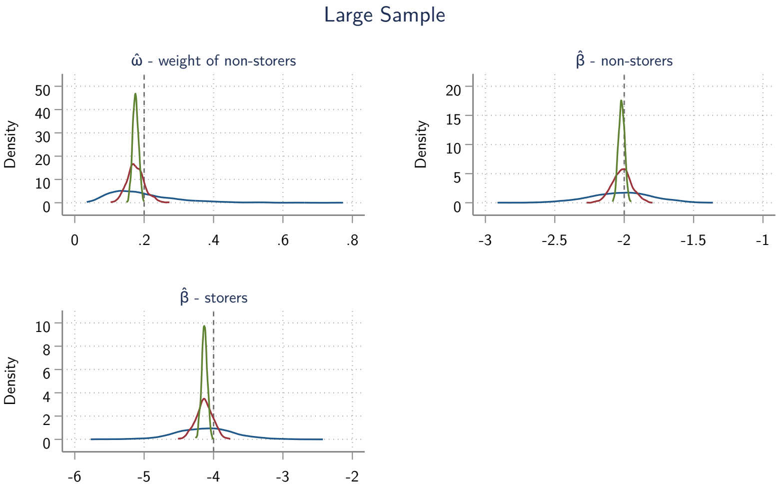

Repetitions = 1000
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  - Linear specification – discarded by Hendel and Nevo (2013) due to negative predicted demand

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- Want to find instruments that satisfy $E(u_t | z_{t-1}, z_t, z_{t+1}) = 0$
- And let GMM push sample analoga of, e.g., $E(u_t)$, $E(z_t u_t)$, $E(z_{t-1} u_t)$, $E(z_{t+1} u_t)$ to zero

Non-additively separable shocks

- Even given suitable instruments there is a practical problem:

$$E[z_t u(\theta)] = \int \int \int z_t(\log Q_t - \widehat{\log Q}_t(P_t, \varepsilon_t, \varepsilon_{t+1}, \theta)) d \Pr(\varepsilon_t)\, d \Pr(\varepsilon_{t+1})\, d \Pr(Q_t, P_t)$$

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- We cannot calculate the sample analog of this moment
- We neither observe $(\varepsilon_t, \varepsilon_{t+1})$, nor can analytically evaluate inner double integral

Method of Simulated Moments

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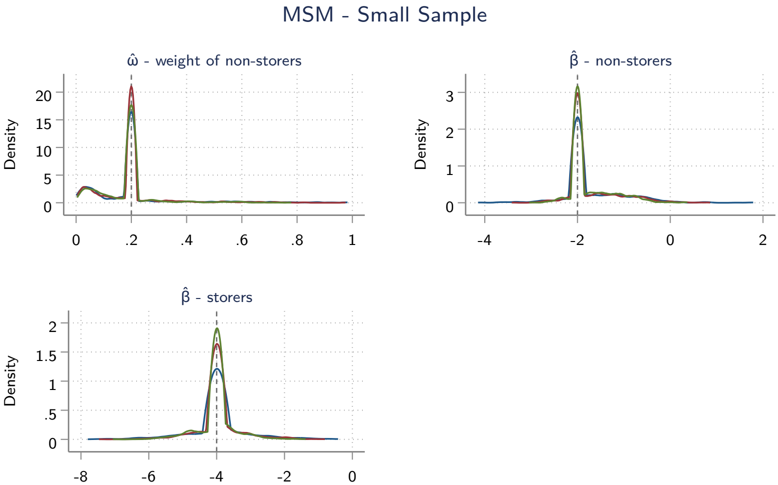
- The algorithm is
  1. Draw s random vectors for ε_t
  2. Fix a candidate parameter vector θ_0
  3. Calculate the simulation analogue of the moment conditions, e.g., $\hat{h}(P_t, \theta) = \frac{1}{s} \sum \log Q_t - \widehat{\log Q}_t(P_t, \varepsilon_t, \varepsilon_{t+1}, \theta_0)$
  4. iterate over 2. and 3. to find the θ^* that pushes the sample analoga of the simulated moments as close to 0 as possible

Simulation of MSM



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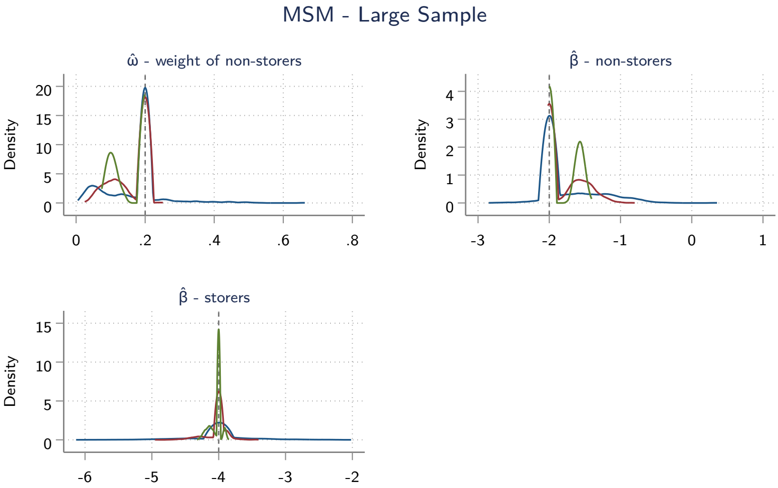

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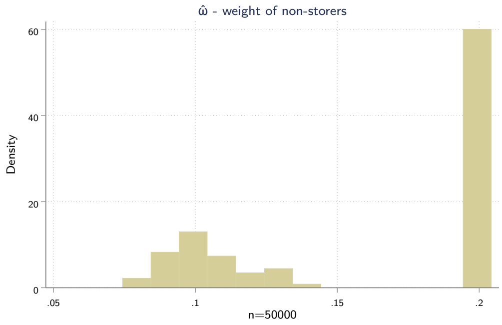
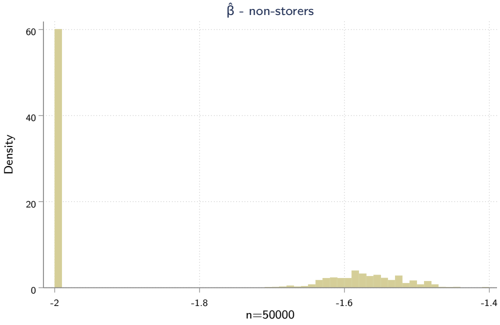
Histogram



$\hat{\omega}$ - weight of non-storers
Density
0
20
40
60
.05
.1
.15
.2
n=50000



$\hat{\beta}$ - non-storers
Density
0
20
40
60
-2
-1.8
-1.6
-1.4
n=50000

Results - Static

Dependent variable	Log(Q)		
	OLS	2SLS	2SLS
log(Price)	-1.23***	-1.931***	-4.75**
	(.243)	(.413)	(1.911)
First Stage Instruments: Cartel Dates, Sugar Tax			
F statistic for IV in first stage		3224	6587
N	308	308	300
Year FE	✓	✓	
Sugar Year FE			✓

Robust standard errors in parenthesis. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Compare with Genesove and Mullin (1998): between approx. -2 and -1 Sugar Year

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Work in Progress

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

$$\frac{\theta}{N} = \eta(P)\frac{P - MC}{P}$$

  Need to

  - estimate elasticity of demand $\eta \rightarrow$ Demand Estimation (75% ✓)
    - Might also use $T > 1$ or Rational Expectations
    - Use MSM with real data, perhaps incorporate importance sampling, or Schennach (2014)
  - estimate price-cost margin $\frac{P-MC}{P} \rightarrow$ Supply Estimation ($\rightarrow$ next)
- Supply and thus Conduct estimation may benefit from taking into account constraints from imports as in Salvo (2010)

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Appendix

Conduct Parameter θ

- *As if* firm j thinks aggregate demand was a function of "conduct" $Q(\theta_j)$
- Then θ shows up in FOC, e.g., for static one-shot Cournot game

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

- θ_j measures deviation from given game like Cournot
- Average θ can be backed out from FOC, say under symmetry

$$\frac{\theta}{N} = \eta \frac{P - MC}{P}$$

- If you know the number of firms, the elasticity of demand η, and price cost margin

Interpretations

1. θ as a reduced-form parameter for *average degree of collusion*

$$\frac{\theta}{N} = \frac{\frac{P-MC}{P}}{\frac{1}{\eta}}$$

Ratio of actual market power over maximum (i.e., monopoly) market power

Advantage over comparing prices | Back

2. Testing firm conduct with general FOC (now renewed interest!) $\theta = 0$ in perfect competition, $\theta = \frac{1}{n}$ in symmetric Cournot $\theta = 1$ in monopoly

3. As if θ captures firms' belief what game is played ("conjectural variation")

Identification of Conduct

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

Four strategies:

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

Classic Intuition why demand rotators identify conduct

Bresnahan (1982)

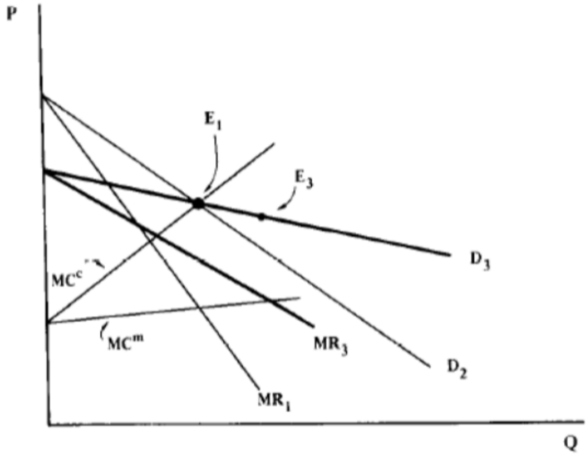
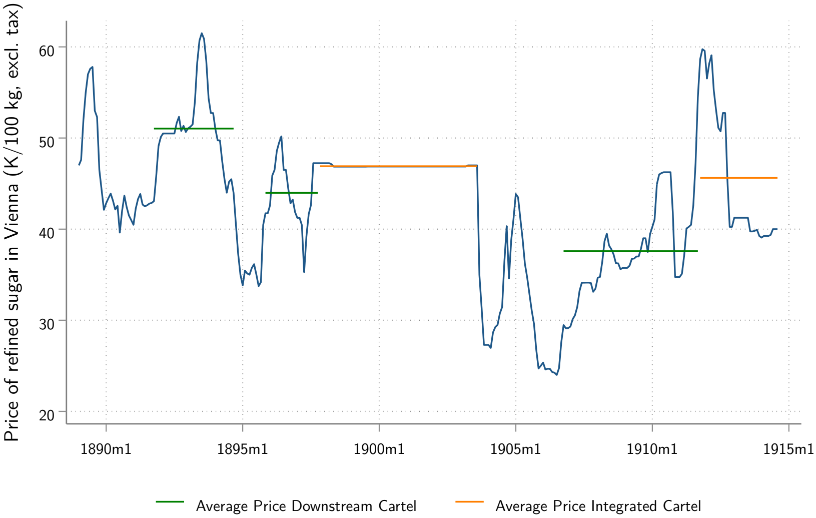
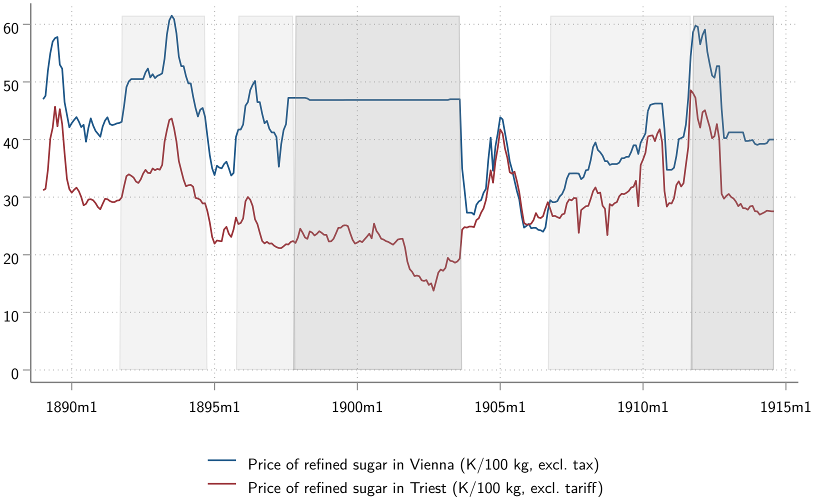


Fig. 2.

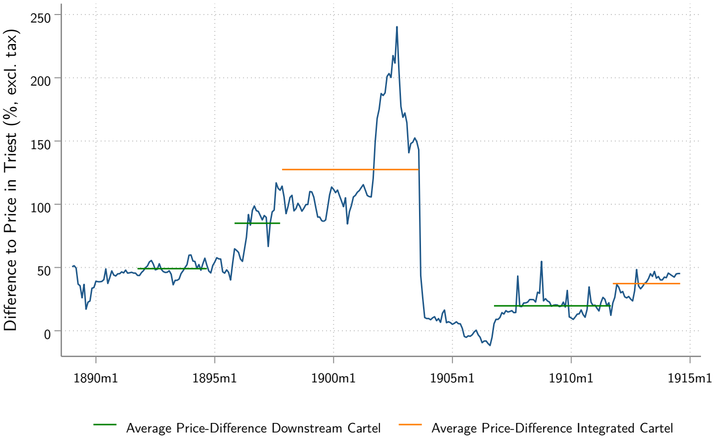
Average prices during cartels (excl. tax)



Comparison with world market price (Triest)

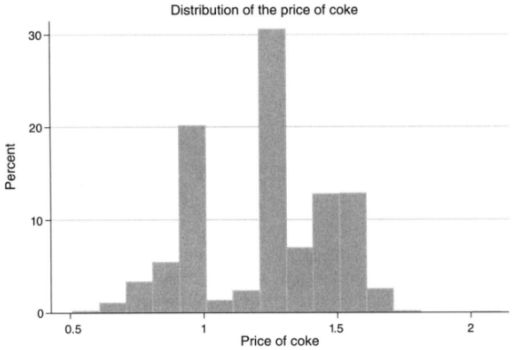


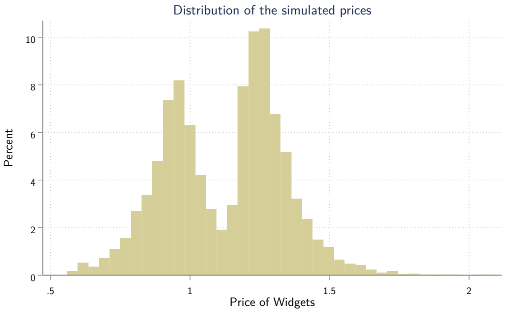
Average difference to world market price (Triest)



Back

Price distribution for Simulation of Hendel & Nevo (2013)





Notes: Mixture of truncated L(0.95, 0.1) and L(1.25, 0.1), N=45,000

Back

Implied long-run elasticity

Long-run elasticity is quantity weighted average of storers and non-storers β Back

$$\frac{\partial Q}{\partial P}\frac{P}{Q} = \frac{\frac{\partial}{\partial P}[\omega e^{\alpha+\beta^n p_t} + (1-\omega)e^{\alpha+\beta^s p_t}]}{Q}P$$

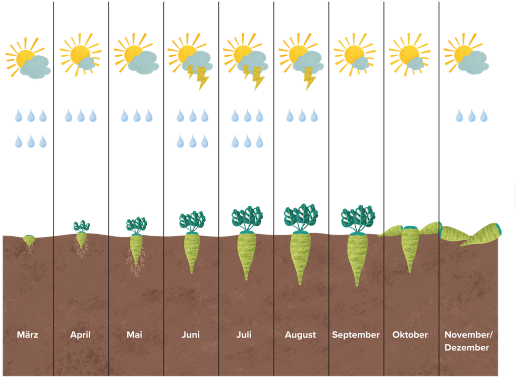
$$= \frac{\beta^n \omega e^{\alpha+\beta^n p_t} + \beta^s(1-\omega)e^{\alpha+\beta^s p_t}}{\omega e^{\alpha+\beta^n p_t} + (1-\omega)e^{\alpha+\beta^s p_t}}P$$

$$= [\beta^n \frac{\omega e^{\alpha+\beta^n p_t}}{\omega e^{\alpha+\beta^n p_t} + (1-\omega)e^{\alpha+\beta^s p_t}} + \beta^s \frac{(1-\omega)e^{\alpha+\beta^s p_t}}{\omega e^{\alpha+\beta^n p_t} + (1-\omega)e^{\alpha+\beta^s p_t}}]P$$

$$= [\beta^n Qshare_n + \beta^s Qshare_s]P$$

Season

- Sugar was produced and thus sold mainly during last quarter of calendar year
- “sugar year” lasting from Sept-Aug captures harvest period (“Kampagne”) Back



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