Homogenous Products

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Fall 2025

Grad IO

Introduction

One of the earliest exercises in econometrics is the estimation of supply and demand for a homogenous product

- According to Stock and Trebbi (2003) IV regression first appeared in a book by Phillip G.
 Wright in 1928 entitled The Tariff on Animal and Vegetable Oils [neatly tucked away in Appendix B: Supply and Demand for Butter and Flaxseed.]
- ▶ Lots of similar studies of simultaneity of supply + demand for similar agricultural products or commodities.

Working (1927)

Supply and Demand For Coffee, everything is linear

$$Q_t^d = \alpha_0 + \alpha_1 P_t + U_t$$

$$Q_t^d = \beta_0 + \beta_1 P_t + V_t$$

$$Q_t^d = Q_t^s$$

Solving for P_t, Q_t :

$$egin{array}{ll} P_t &=& rac{eta_0-lpha_0}{lpha_1-eta_1} + rac{V_t-U_t}{lpha_1-eta_1} \ Q_t &=& rac{lpha_1eta_0-lpha_0eta_1}{lpha_1-eta_1} + rac{lpha_1V_t-eta_1U_t}{lpha_1-eta_1} \end{array}$$

Price is a function of both error terms, and we can't use a clever substitution to cancel things out.

Working (1927)

To make things really obvious:

$$Cov(P_t, U_t) = -rac{Var(U_t)}{lpha_1 - eta_1} \ Cov(P_t, V_t) = rac{Var(V_t)}{lpha_1 - eta_1}$$

▶ When demand slopes down ($\alpha_1 < 0$) and supply slopes up ($\beta_1 > 0$) then price is positively correlated with demand shifter U_t and negatively correlated with supply shifter V_t .

Working (1927)

$$Cov(P_t, Q_t) = \alpha_1 Var P_t + Cov(P_t, U_t)$$

 $Cov(P_t, Q_t) = \beta_1 Var P_t + Cov(P_t, V_t)$

- ▶ Bias in OLS estimate (Demand) $Bias(\alpha_1) = \frac{Cov(P_t, U_t)}{VarP_t}$.
- ▶ Bias in OLS estimate (Supply) $Bias(\beta_1) = \frac{Cov(P_t, V_t)}{VarP_t}$.
- We can actually write both this way when $Cov(U_t, V_t) = 0$:

OLS Estimate
$$=rac{lpha_1 Var(V_t) + eta_1 Var(U_t)}{Var(V_t) + Var(U_t)}$$

- ▶ More variation in supply V_t → better estimate of demand.
- ▶ More variation in demand U_t → better estimate of supply.
- ▶ Led Working to say the statistical demand function (OLS) is not informative about the economic demand function (or supply function).

Simultaneity

- ▶ For most of you, this was probably a review.
- ▶ We know what the solution is going to be to the simultaneity problem.
- ▶ We need an excluded instrument that shifts one curve without affecting the other.
- ▶ We can use this to form a 2SLS estimate.
- ▶ Instead let's look at something a little different...

Simultaneity and Identification

Angrist, Imbens, and Graddy (ReStud 2000).

- ▶ Demand for Whiting (fish) at Fulton Fish Market
- ▶ Do not place functional form restrictions on demand (log-log, log-linear, linear, etc.).
- "What does linear IV regression of Q on P identify, even if the true (but unknown) demand function is nonlinear"
- ► Takes a program evaluation/treatment effects approach to understanding the "causal effect" of price on quantity demanded.
- ▶ Aside: Is there even such a thing as the causal effect of price on quantity demanded?

Four Cases

Ranked in increasing complexity

1. Linear system with constant coefficients

$$egin{array}{lll} q_t^d(p,z,x) &=& lpha_0 + lpha_1 p + lpha_2 z + lpha_3 x + \epsilon_t \ q_t^s(p,z,x) &=& eta_0 + eta_1 p + eta_2 z + eta_3 x + \eta_t \end{array}$$

2. Linear system with non-constant coefficients

$$\begin{array}{lcl} q_t^d(p,z,x) & = & \alpha_{0t} + \alpha_{1t}p + \alpha_{2t}z + \alpha_{3t}x + \epsilon_t \\ q_t^s(p,z,x) & = & \beta_{0t} + \beta_{1t}p + \beta_{2t}z + \beta_{3t}x + \eta_t \end{array}$$

3. Nonlinear system with constant shape (separable)

$$egin{array}{lll} q_t^d(p,z,x) &=& q^d(p,z,x) + \epsilon_t \ q_t^s(p,z,x) &=& q^s(p,z,x) + \eta_t \end{array}$$

4. Nonlinear system with time-varying shape (non-separable)

$$\begin{array}{lcl} q_t^d(p,z,x) & = & q^d(p,z,x,\epsilon_t) \\ q_t^s(p,z,x) & = & q^s(p,z,x,\eta_t) \end{array}$$

AIG: Heterogeneity

Two kinds:

- 1. Heterogeneity depending on value of p fixing t (only relevant in nonlinear models)
- 2. Heterogeneity across t, fixing p (cases 2 and 4).
- ▶ The problem is that we don't generality know which kind of heterogeneity we face.
- ▶ Is case (4) hopeless? Or what can we expect to learn?
- ▶ Even econometricians struggle with non-linear non-separable models (!)

AIG: Assumptions

Assume binary instrument $z_t \in \{0, 1\}$ to make things easier.

- 1. Regularity conditions on q_t^d , q_t^s , p_t , z_t , w_t first and second moment and is stationary, etc.
 - $q_t^d(p,z,x)$, $q_t^s(p,z,x)$ are continuously differentiable in p.
- 2. z_t is a valid instrument in q_t^d
 - ightharpoonup Exclusion: for all p, t

$$q_t^d(p,z=1,x_t)=q_t^d(p,z=0,x_t)\equiv q_t^d(p,x_t)$$

ie: conditioning on p_t means no dependence on z_t

- Relevance: for some period t: q^s_t(p_t, 1, x_t) ≠ q^s_t(p_t, 0, x_t).
 ie: z_t actually shifts supply somewhere!
- ▶ Independence: ϵ_t , η_t , z_t are mutually independent conditional on x_t .

Wald Estimator

Focus on the simple case:

- ▶ $z \in \{0, 1\}$ where 1 denotes "stormy at sea" and 0 denotes "calm at sea"
- ▶ Idea is that offshore weather makes fishing more difficult but doesn't change onshore demand.
- ▶ Ignore x (for now at least) or assume we condition on each value of x.

$$\hat{\alpha}_{1,0} \rightarrow^p \frac{\mathbb{E}[q_t|z_t=1] - \mathbb{E}[q_t|z_t=0]}{\mathbb{E}[p_t|z_t=1] - \mathbb{E}[p_t|z_t=0]} \equiv \alpha_{1,0}$$

- If we are in case (1) then we are good. In fact, any IV gives us a consistent estimate of α_1
- ▶ If we are in case (4) then $\alpha_{1,0}$ the object we recover, is not an estimator of a structural parameter.
- ▶ Moreover, this is at best a LATE, and thus it differs depending on which instrument we use!

AGI: Negative Results

- ▶ Should we divorce structural estimation from estimating "deep" population parameters (as suggested by Lucas critique)?
- ▶ Authors make the point that IV estimator identifies something about relationship between p and q, without identifying deep structural parameters?
- ▶ In IO this is a somewhat heretical idea (especially to start the course with).

AGI: Structural Interpretation

In order to interpret the Wald estimator $\alpha_{1,0}$ we make some additional economic assumptions on the structure of the problem:

- 1. Observed price is market clearing price $q_t^d(p_t) = q_t^s(p_t, z_t)$ for all t. (This means no frictions!).
- 2. "Potential prices": for each value of z there is a unique market clearing price

$$\forall z,t: \tilde{p}(z,t) \text{ s.t. } q_t^d(\tilde{p}(z,t)) = q_t^s(\tilde{p}(z,t),z).$$

 $\tilde{p}(z,t)$ is the potential price under any counterfactual (z,t)

AGI: Structural Interpretation

- ▶ Just like in IV we need denominator to be nonzero so that $E[p_t|z_t = 1] \neq E[p_t|z_t = 0]$.
- ▶ Other key assumption is the familiar monotonicity assumption
 - $\tilde{p}(z,t)$ is weakly increasing in z.
 - ▶ Just like in program evaluation this is the key assumption. There it rules out "defiers" here it allows us to interpret the average slope as $\alpha_{1,0}$.
 - Assumption is untestable because you do not observe both potential outcomes $\tilde{p}(0,t)$ and $\tilde{p}(1,t)$ (same as in program evaluation).
 - ▶ Any story about IV is just a story! (Always the case!) unless we have repeated observations on the same individual.

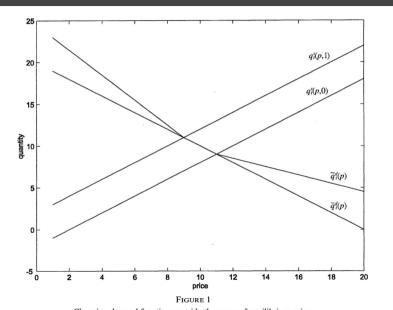
AGI: Lemma 1

The key result establishes that the numerator of $\alpha_{1,0}$:

$$\mathbb{E}[q_t|z_t=1] - \mathbb{E}[q_t|z_t=0] = \mathbb{E}_t\left[\int_{ ilde{p}(0,t)}^{ ilde{p}(1,t)} rac{\partial q_t^d(s)}{\partial s} d\, s
ight]$$

- For each t we average over the slope of demand curve among the two potential prices: $\int_{\tilde{p}(0,t)}^{\tilde{p}(1,t)} \frac{\partial q_t^t(s)}{\partial s} ds$
- ▶ This range could differ for each t.
- ightharpoonup Then we average this average over all t.

AGI: Figure



AGI: Takeaways

What did we learn?

- $\alpha_{1,0}$ only provides information about demand curve in range of potential price variation induced by the instrument.
- ▶ Don't know anything about demand curve outside this range!
- For different instruments z, $\alpha_{1,0}$ has a different interpretation like the LATE does. (Different from the linear model where anything works!).
- ▶ This is a bit weird: different cost shocks could trace out different paths along the demand curve—why do we care if price change came from a tax change or an input price change? Are they tracing out different subpopulations?
- ▶ We need monotonicity so that we know the range of integration $\tilde{p}(0,t) \rightarrow \tilde{p}(1,t)$ instead of $\tilde{p}(1,t) \rightarrow \tilde{p}(0,t)$
- ▶ Observations where $\tilde{p}(0,t) = \tilde{p}(1,t)$ don't factor into the average but we don't know what these observations are because potential prices are unobserved! What is the relevant sub-sample?

AGI: Nonlinear IV

- given t average the slope of q_t^{d} from $\tilde{p}(0,t)$ to $\tilde{p}(1,t)$
- given price $s \in [\tilde{p}(0,t), \tilde{p}(1,t)]$ average $q_t^d(s)$ across t. (randomness is due to ϵ_t).
- ▶ Weight $\omega(s)$ is not a function of t but it is largest for prices most likely to fall between $\tilde{p}(0,t)$ and $\tilde{p}(1,t)$.
- ► Case (2): $q_t^d(p) = \alpha_{0t} + \alpha_{1t}p + \epsilon_t$. $\alpha_{1,0} = \frac{\mathbb{E}[\alpha_{1t}(\tilde{p}(1,t) \tilde{p}(0,t))]}{\mathbb{E}\tilde{\alpha}(1,t) \mathbb{E}\tilde{\alpha}(0,t)} \neq \mathbb{E}\alpha_{1,t}$

We need mean independence

AGI: Nonlinear IV

 \blacktriangleright Suppose we had a continuous z instead, now we can do a full nonparametric IV estimator.

$$a(z) = \lim_{\nu \to 0} \frac{\mathbb{E}(q_t|z) - \mathbb{E}(q_t|z - \nu)}{\mathbb{E}(p_t|z) - \mathbb{E}(p_t|z - \nu)}$$

• Use a kernel to estimate $\hat{q}|z$ and $\hat{p}|z$

$$lpha'(z) = rac{\hat{q}'(z)}{\hat{p}'(z)} pprox rac{\hat{q}'(z+h) - \hat{q}(z)}{\hat{p}'(z+h) - \hat{p}(z)}$$

AGI: Takeaways

- ▶ When you have a parametric model, you don't need these results because we can define whatever (nonlinear) parametric functional form we want.
- ▶ There we will focus on parsimonious and realistic parametric functional forms. (this is the rest of the course)
- ▶ If we don't have a parametric model, then these show us that linear IV estimators give us some average (a particular one!) of slopes.
- ▶ Caveat: this only works for a single product. In the multi-product case things are a lot more complicated
 - ▶ For multiproduct oligopoly it is much harder to satisfy the monotonicity condition. Why?