Industry Dynamics and Productivity II

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Empirical IO
Winter 2015

"The Dynamics of Productivity in the Telecommunications Equipment Industry"
Olley and Pakes (1996)

Overview

- Analyzes effects of deregulation in telecommunications equipment industry.
- Deregulation increases productivity, primarily through reallocation toward more productive establishments.
- Estimation approach deals with simultaneity and selection issues.

Background I

- AT&T had a monopoly on telecommunications services in the US throughout most of the 20th century (note: a telecommunications network is a classic example of a natural monopoly).
- Before the regulatory change, AT&T required that equipment attached to their network must be supplied by the AT&T, and virtually all of their equipment was supplied by their subsidiary, Western Electric. Thus, they leveraged their network monopoly to a monopoly on phones.

Background II

- A change in technology opened up new markets for telecommunications equipment (e.g., fax machines)
- Meanwhile, the FCC (regulatory agency) decided to begin allowing the connection of privately-provided devices to AT&T's network.
- A surge of entry into telecommunications equipment manufacturing followed in the late 1960's and 1970's.

TABLE I

CHARACTERISTICS OF THE DATA

Year	Plants	Firms	Shipments (billions 1982 $)	Employment
1963	133	104	5.865	136899
1967	164	131	8.179	162402
1972	302	240	11.173	192248
1977	405	333	13.468	192259
1982	473	375	20.319	222058
1987	584	481	22.413	184178

Background III

- AT&T continued purchasing primarily from Western Electric into the 1980's (although consumers were free to purchase devices from other companies).
- The divestiture (breakup) of AT&T created seven regional Bell companies that were no longer tied to Western Electric, and they were prohibited from manufacturing their own equipment.
- The divestiture was implemented in January 1984. Western Electric's share dropped dramatically.

TABLE II

BELL COMPANY EQUIPMENT PROCUREMENT
(PERCENT PURCHASED FROM WESTERN ELECTRIC)

1982	1983	1984	1985	1986[E]
92.0	80.0	71.8	64.2	57.6

[E] Estimated for 1986.
Source: NTIA (1988, p. 336, and discussion pp. 335–337).

Entry

TABLE III

ENTRANTS ACTIVE IN 1987

	Number	Share of Number Active in 1987 (%)	Share of 1987 Shipments (%)	Share of 1987 Employment (%)
Plants: New since 1972	463	79.0	32.8	36.0
Firms: New since 1972	419	87.0	30.0	41.4
Plants: New since 1982	306	52.0	12.0	13.5
Firms: New since 1982	299	60.1	19.4	27.5

Exit

TABLE IV

INCUMBENTS EXITING BY 1987

	Number	Share of Number Active in Base Year (%)	Share of Shipments in Base Year (%)	Share of Employment in Base Year (%)
Plants active in 1972 but not in 1987	181	60.0	40.2	39.0
Firms active in 1972 but not in 1987	169	70.0	13.8	12.1
Plants active in 1982 but not in 1987	195	41.2	26.0	24.1
Firms active in 1982 but not in 1987	184	49.1	17.3	16.1

The model

- Incumbent firms (i) make three decisions:
  - Whether to exit or continue. If they exit, they receive a fixed scrap value Ψ and never return.
  - If they stay, they choose labor l_{it},
  - and investment i_{it}.
- Capital accumulation:

$$k_{t+1} = (1 - \delta)\, k_t + i_t$$

- Another state variable is age: $a_{t+1} = a_t + 1$

Production

- They assume the following Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}$$

  where y_{it} is output, k_{it} is capital, l_{it} is labor, ω_{it} is a persistant component of productivity, and η_{it} is a transient shock to productivity.
- Productivity evolves according to a Markov process: $F(\cdot|\omega)$.
- η is either measurement error, or there is no information about it when labor decisions are made.

Equilibrium behavior

- They assume the existence of a Markov perfect equilibrium. Market structure and prices are state variables in the MPE, but they are common across firms, so they can be absorbed into time subscripts for the value function:

$$\begin{aligned} V_t(\omega_t, a_t, k_t) = \quad & \max\Big\{\Psi, \sup_{i_t \geq 0} \pi_t(\omega_t, a_t, k_t) - c(i_t) \\ & +\beta E\left[V_{t+1}(\omega_{t+1}, a_{t+1}, k_{t+1}) \,|\, J_t\right] \end{aligned}$$

  where J_t represents the information set at time t.

- Equilibrium strategies can be decribed by functions $\underline{\omega}_t(a_t, k_t)$ and $i_t(\omega_t, a_t, k_t)$.
  - A firm will continue if and only if $\omega \geq \underline{\omega}_t(a_t, k_t)$.
  - Continuing firms invest $i_t = i_t(\omega_t, a_t, k_t)$

Aside: Markov perfect equilibrium

- It's worth defining Markov perfect equilibrium, as it will come up repeatedly in the course.
- Loosely, it means a subgame perfect equilibrium in which strategies are functions of "real" (payoff relevant) state variables.
- This rules out conditioning on variables that don't impact present or future payoffs. For example, in the repeated prisoner's dilemma, cooperation with grim trigger punishments is ruled out.
- Markov perfect equilibrium is to dynamic games what perpetual static Nash is to repeated games.

Thinking about bias

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  - Up: when productivity is high, a firm will use more labor
- How does selection due to exit bias the capital coefficient estimate?
  - Down: firms with high capital have lower cutoffs $\underline{\omega}_t$ for exit. Thus, conditional on survival, there is a negative correlation between k and ω

Productivity inversion

- In a technical paper, Pakes (1994) shows that optimal investment $i_t\left(\omega_t, a_t, k_t\right)$ is monotonically increasing in ω_t, provided $i_t > 0$.
- Given monotonicity, optimal investment can be inverted for productivity:

$$\omega_{it} = h_t\left(i_{it}, a_{it}, k_{it}\right).$$

- We're going to talk more about the $i_t > 0$ requirement with Levinsohn and Petrin (2003).

First stage model

- Substituting in the inversion function,

$$y_{it} = \beta_l l_{it} + \phi_t \left(i_{it}, a_{it}, k_{it} \right) + \eta_{it}$$

where

$$\phi_t \left(i_{it}, a_{it}, k_{it} \right) = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + h_t \left(i_{it}, a_{it}, k_{it} \right)$$

- We can estimate this equation using a semiparametric regression. This may identify β_l, but not the other coefficients.
- With Ackerberg, Caves, and Frazer (2006), we will think more carefully about what's identifying β_l, but don't worry about it for now.

First stage output

- With $\hat{\beta}_l$, we can also estimate ϕ:

$$\hat{\phi}_{it} = y_{it} - \hat{\beta}_l l_{it}$$

- So far we have estimates of β_l and ϕ. $\beta_k k$ and ω are both in the control function ϕ, and we would like to separate them. We're going to use the Markov assumption on ω for identification.

Identifying β_k,β_a

- Let's first think about how to do this without worrying about exit. Define

$$g\left(\omega_{i,t-1}\right) = E\left[\omega_{i,t}|\omega_{i,t-1}\right],$$

so that

$$\omega_{i,t} = g\left(\omega_{i,t-1}\right) + \xi_{i,t}$$

where $\xi_{i,t+1}$ is the innovation (unexpected change) to productivity.

- We can write out a second stage regression equation:

$$\phi_{i,t} = \beta_k k_{it} + \beta_a a_{it} + g\left(\omega_{i,t-1}\right) + \xi_{i,t}$$

and note that $\omega_{i,t-1}$ can also be written as a function of (β_k, β_a):

$$\phi_{i,t} = \beta_k k_{it} + \beta_a a_{it} + g\left(\phi_{i,t-1} - \beta_k k_{i,t-1} - \beta_a a_{i,t-1}\right) + \xi_{i,t}$$

Identifying β_k,β_a

- Second stage regression equation:

$$\phi_{i,t} = \beta_k k_{it} + \beta_a a_{it} + g\left(\phi_{i,t-1} - \beta_k k_{i,t-1} - \beta_a a_{i,t-1}\right) + \xi_{i,t}$$

- One way to think about this: once we specify a parametric function for g, this basically becomes OLS.
- NLLS: we can guess values of (β_k, β_a), (nonparametrically) estimate g conditional on those value of (β_k, β_a), and then back out $\xi_{i,t}(\beta_k, \beta_a)$. Search over (β_k, β_a) to minimize sum of squares of $\xi_{i,t}(\beta_k, \beta_a)$.

Selection

- Let $P_t = Pr\left(\chi_{t+1} = 1 | \underline{\omega}_{t+1}\left(k_{t+1}, a_{t+1}\right), J_t\right)$ be the propensity score for exit.
- As long as the conditional density of ω_{t+1} has full support, this can be inverted to express $\underline{\omega}_{t+1} = f\left(P_t, \omega_t\right)$

The second stage with selection

- Write the expectation of $y_{t+1} - \beta_l l_{t+1}$ conditional on survival:

$$E\left[y_{t+1} - \beta_l l_{t+1} | a_{t+1}, k_{t+1}, \chi_{t+1} = 1\right]$$

$$= \beta_a a_{t+1} + \beta_k k_{t+1} + g\left(\underline{\omega}_{t+1}, \omega_t\right)$$

where $g\left(\underline{\omega}_{t+1}, \omega_t\right) = E\left[\omega_{t+1} | \omega_t, \chi_{t+1} = 1\right]$

- Using the inversion of the selection probability, we can write

$$g\left(\underline{\omega}_{t+1}, \omega_t\right) = g\left(f\left(P_t, \omega_t\right), \omega_t\right)$$

which can be written more simply as $g\left(P_t, \omega_t\right)$.

Final step

- Conditional on values of (β_a, β_k), we can construct an estimate of $\omega_t = \phi_t - \beta_a a_t - \beta_k k_t$
- Finally, write

$$\begin{aligned} y_{t+1} - \beta_l l_{t+1} = \;& \beta_a a_{t+1} + \beta_k k_{t+1} + g\left(P_t, \phi_t - \beta_a a_t - \beta_k k_t\right) \\ & + \xi_{t+1} + \eta_{t+1} \end{aligned}$$

- Again, we can use NLLS to estimate (β_k, β_a).
- Note that $E\left(\xi_{i,t} l_{i,t}\right) \neq 0$ is what creates the need for the first stage.

Estimation steps

1. First stage semi-parametric regression:

$$y_{it} = \beta_l l_{it} + \phi_t \left(i_{it}, a_{it}, k_{it} \right) + \eta_{it}$$

2. Estimate propensity scores: $P_t = Pr \left(\chi_{t+1} = 1 | \underline{\omega}_{t+1} \left(k_{t+1}, a_{t+1} \right), J_t \right)$

3. Estimate remaining parameters:

$$\begin{aligned} y_{t+1} - \beta_l l_{t+1} = \quad & \beta_a a_{t+1} + \beta_k k_{t+1} + g \left(P_t, \phi_t - \beta_a a_t - \beta_k k_t \right) \\ & + \xi_{t+1} + \eta_{t+1} \end{aligned}$$

using fact that innovation term ξ_{t+1} is mean-uncorrelated with variables determined at t, including k_{t+1}.

TABLE VI

ALTERNATIVE ESTIMATES OF PRODUCTION FUNCTION PARAMETERS[a]
(STANDARD ERRORS IN PARENTHESES)

Sample:	Balanced Panel		Full Sample[c, d]						
								Nonparametric F_ω	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation Procedure	Total	Within	Total	Within	OLS	Only P	Only h	Series	Kernel
Labor	.851 (.039)	.728 (.049)	.693 (.019)	.629 (.026)	.628 (.020)			.608 (.027)	
Capital	.173 (.034)	.067 (.049)	.304 (.018)	.150 (.026)	.219 (.018)	.355 (.02)	.339 (.03)	.342 (.035)	.355 (.058)
Age	.002 (.003)	−.006 (.016)	−.0046 (.0026)	−.008 (.017)	−.001 (.002)	−.003 (.002)	.000 (.004)	−.001 (.004)	.010 (.013)
Time	.024 (.006)	.042 (.017)	.016 (.004)	.026 (.017)	.012 (.004)	.034 (.005)	.011 (.01)	.044 (.019)	.020 (.046)
Investment	—	—	—	—	.13 (.01)	—	—	—	—
Other Variables	—	—	—	—	—	Powers of P	Powers of h	Full Polynomial in P and h	Kernel in P and h
# Obs.[b]	896	896	2592	2592	2592	1758	1758	1758	1758

- Why do within estimators have lower capital coefficients?

TABLE IX

INDUSTRY PRODUCTIVITY GROWTH RATES[a]

Time Period	(1) Full Sample	(2) Balanced Panel
1974–1975	−.279	−.174
1975–1977	.020	−.015
1978–1980	.146	.102
1981–1983	−.087	−.038
1984–1987	.041	.069
1974–1987	.008	.020
1975–1987	.032	.036
1978–1987	.034	.047

[a]The numbers in Table IX are annual averages over the various subperiods.

- Estimate of productivity: $p_{it} = \exp\left(y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_a a_{it}\right)$
- Plants that eventually exit have low productivity growth
- New entrants tend to have lower productivity than continuing establishments
- Surviving entrants tend to have greater average productivity growth than incumbents.

Productivity decomposition

- Aggregate productivity: $p_t = \sum_{i=1}^{N_t} s_{it} p_{it}$.
- Can be decomposed as follows:

$$\begin{aligned} p_t &= \sum_{i=1}^{N_t} \left(\bar{s}_t + \Delta s_{it}\right)\left(\bar{p}_t + \Delta p_{it}\right) \\ &= N_t \bar{s}_t \bar{p}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta p_{it} \\ &= \bar{p}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta p_{it} \end{aligned}$$

  where $\bar{p}_t$ are unweighted mean productivity and shares in the cross-section.

- Thus, aggregate productivity decomposes into an unweighted mean and a covariance term.

TABLE XI

DECOMPOSITION OF PRODUCTIVITY[a]
(EQUATION (16))

Year	p_t	$\bar{p}_t$	$\Sigma_i \Delta s_{it} \Delta p_{it}$	$\rho(p_t, k_t)$
1974	1.00	0.90	0.01	−0.07
1975	0.72	0.66	0.06	−0.11
1976	0.77	0.69	0.07	−0.12
1977	0.75	0.72	0.03	−0.09
1978	0.92	0.80	0.12	−0.05
1979	0.95	0.84	0.12	−0.05
1980	1.12	0.84	0.28	−0.02
1981	1.11	0.76	0.35	0.02
1982	1.08	0.77	0.31	−0.01
1983	0.84	0.76	0.08	−0.07
1984	0.90	0.83	0.07	−0.09
1985	0.99	0.72	0.26	0.02
1986	0.92	0.72	0.20	0.03
1987	0.97	0.66	0.32	0.10

[a] See text for details.

"Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants"
Nina Pavcnik (2002)

Overview

- First application of OP, and early paper in what is now a massive structural literature on trade liberalization and productivity.
- Investigates effects of "massive trade liberalization" in Chile from late 70's to early 80's.
- The Pinochet regime was tumultuous, and there was a large recession in 82-83, so a simple before/after comparison wouldn't be plausible.
- Combines structural estimation with diff-in-diffs identification strategy
  - before vs. after trade liberalization
  - sectors affected by trade liberalization vs. non-traded goods industries

Findings

- Consistent with OP, selection and simultaneity bias substantially bias estimates of the coefficients of the production function
- Substantial within-plant productivity improvements
- There was massive exit during the period of liberalization, and exiting plants tended to be less productive

TABLE 1

Plants active in 1979 but not in 1986

Trade orientation	Share of plants	Share of labour	Share of capital	Share of investment	Share of value added	Share of output
Exiting plants of a given trade orientation as a share of all plants active in 1979						
All trade orientations	0·352	0·252	0·078	0·135	0·155	0·156
Export-oriented	0·045	0·049	0·009	0·039	0·023	0·023
Import-competing	0·141	0·108	0·029	0·047	0·068	0·065
Nontraded	0·165	0·095	0·040	0·049	0·064	0·067
Exiting plants of a given trade orientation as a share of all exiting plants						
Export-oriented	0·129	0·194	0·117	0·289	0·149	0·148
Import-competing	0·401	0·429	0·369	0·350	0·436	0·419
Nontraded	0·470	0·377	0·513	0·361	0·415	0·432
Exiting plants of a given trade orientation as a share of all plants active in 1979 in the corresponding trade sector						
Export-oriented	0·416	0·298	0·030	0·172	0·121	0·128
Import-competing	0·383	0·263	0·093	0·149	0·183	0·211
Nontraded	0·316	0·224	0·104	0·107	0·147	0·132

Note: This figure also includes plants that exited after the end of 1979, but before the end of 1980 and were excluded in the estimation because of missing capital variable.

- massive exit

Some details

- Methodologically almost identical to Olley and Pakes.
- One difference: while OP use value added as output, Pavcnik uses sales and includes materials on the right-hand side:

$$y_{it} = \beta_0 + \beta x_{it} + \beta_k k_{it} + e_{it}$$

  where x includes unskilled labor, skilled labor, and material inputs.
- In the first-stage regression, she estimates β, i.e., the coefficients on the labor and materials variables.
- Zero investment is a significant phenomenon in the data, and she finds it doesn't matter whether she drops observations with $i_{it} = 0$ or if she ignores the monotonicity issue and includes them.

More details

- Sales deflated using price indices for four-digit industry codes. Note that this leaves A LOT of room for price heterogeneity. Things that are four-digit industries:
  - Manufacture of malt liquors and malt
  - Manufacture of consumer electronics
  - Manufacture of motor vehicles
- When estimating relationship between trade and productivity, she controls for heterogeneous prices/markups using plant-specific fixed effects.
- Estimates model separately for each 2- or 3-digit industry.

TABLE 2

Estimates of production functions

		Balanced panel				Full sample					
		OLS		Fixed effects		OLS		Fixed effects		Series	
		(1)		(2)		(3)		(4)		(5)	
		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Food processing	Unskilled labour	0·152	0·007	0·185	0·012	0·178	0·006	0·210	0·010	0·153	0·007
	Skilled labour	0·127	0·006	0·027	0·008	0·131	0·006	0·029	0·007	0·098	0·009
	Materials	0·790	0·004	0·668	0·008	0·763	0·004	0·646	0·007	0·735	0·008
	Capital	0·046	0·003	0·011	0·007	0·052	0·003	0·014	0·006	0·079	0·034
	N	6432				8464				7085	
Textiles	Unskilled labour	0·187	0·011	0·240	0·017	0·229	0·009	0·245	0·015	0·215	0·012
	Skilled labour	0·184	0·010	0·088	0·014	0·183	0·009	0·088	0·012	0·177	0·011
	Materials	0·667	0·007	0·564	0·011	0·638	0·006	0·558	0·009	0·637	0·097
	Capital	0·056	0·005	0·015	0·012	0·059	0·004	0·019	0·011	0·052	0·034
	N	3689				5191				4265	
Wood	Unskilled labour	0·233	0·016	0·268	0·026	0·247	0·013	0·273	0·022	0·195	0·015
	Skilled labour	0·121	0·015	0·040	0·021	0·146	0·012	0·047	0·018	0·130	0·014
	Materials	0·685	0·010	0·522	0·014	0·689	0·008	0·554	0·011	0·679	0·010
	Capital	0·055	0·007	0·023	0·018	0·050	0·006	−0·002	0·016	0·101	0·051
	N	1649				2705				2154	
Paper	Unskilled labour	0·218	0·024	0·258	0·033	0·246	0·021	0·262	0·029	0·193	0·024
	Skilled labour	0·190	0·018	0·022	0·027	0·180	0·016	0·050	0·023	0·203	0·018
	Materials	0·624	0·013	0·515	0·025	0·597	0·011	0·514	0·021	0·601	0·014
	Capital	0·074	0·010	0·031	0·025	0·085	0·009	0·031	0·023	0·068	0·018
	N	1039				1398				1145	

Diff-in-diffs

- After estimating productivity, she estimates the following regression:

  $$pr_{it} = \alpha_0 + \alpha 1(Time)_{it} + \alpha_2(Trade)_{it} + \alpha_3(Trade * Time)_{it} + \alpha_4 Z_{it} + \nu_{it}$$

  where *Time* includes time dummies and *Trade* includes indicators for the firm's sector.

- Idea is that year dummies capture omitted macroeconomic variables. We're hoping that different sectors don't have heterogeneous responses to macroeconomic shocks.

TABLE 4

Estimates of equation 12

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Export-oriented	0·106	0·030**	0·106	0·030**	0·112	0·031**	0·098	0·048**	0·095	0·048**	0·100	0·046**
Import-competing	0·105	0·021**	0·105	0·021**	0·103	0·021**	−0·024	0·040	−0·025	0·040	−0·007	0·039
ex_80	−0·054	0·025**	−0·053	0·025**	−0·055	0·025**	−0·071	0·026**	−0·068	0·026**	−0·071	0·026**
ex_81	−0·099	0·028**	−0·097	0·028**	−0·100	0·028**	−0·117	0·027**	−0·110	0·027**	−0·119	0·027**
ex_82	0·005	0·032	0·007	0·032	0·003	0·032	−0·054	0·028*	−0·042	0·028	−0·055	0·028*
ex_83	0·021	0·032	0·023	0·032	0·021	0·032	−0·036	0·029	−0·025	0·030	−0·038	0·029
ex_84	0·050	0·031	0·051	0·031	0·050	0·031	0·007	0·028	0·017	0·028	0·007	0·028
ex_85	0·030	0·030	0·032	0·031	0·028	0·030	−0·001	0·029	0·013	0·030	−0·003	0·029
ex_86					0·043	0·036					−0·008	0·034
im_80	0·011	0·014	0·011	0·014	0·010	0·014	0·013	0·014	0·013	0·014	0·013	0·014
im_81	0·047	0·015**	0·047	0·015**	0·046	0·015**	0·044	0·014**	0·044	0·014**	0·044	0·014**
im_82	0·033	0·016**	0·034	0·017**	0·030	0·016*	0·024	0·015*	0·024	0·015*	0·025	0·015*
im_83	0·042	0·017**	0·043	0·017**	0·043	0·017**	0·040	0·015**	0·041	0·015**	0·042	0·015**
im_84	0·062	0·017**	0·062	0·017**	0·063	0·017**	0·059	0·015**	0·059	0·015**	0·061	0·015**
im_85	0·103	0·017**	0·104	0·017**	0·104	0·017**	0·101	0·015**	0·102	0·016**	0·101	0·015**
im_86					0·071	0·019**					0·073	0·017**
Exit indicator	−0·081	0·011**	−0·076	0·014**			−0·019	0·010**	−0·010	0·013		
Exit_export indicator			−0·021	0·036					−0·069	0·035*		
Exit_import indicator			−0·007	0·023					−0·005	0·021		
Industry indicators	yes		yes		yes		yes		yes		yes	
Plant indicators	no		no		no		yes		yes		yes	
Year indicators	yes		yes		yes		yes		yes		yes	
R^2 (adjusted)	0·057		0·058		0·062		0·498		0·498		0·488	
N	22983		22983		25491		22983		22983		25491	

Note: ** and * indicate significance at a 5% and 10% level, respectively. Standard errors are corrected for heteroscedasticity. Standard errors in columns 1–3 are also adjusted for repeated observations on the same plant. Columns 1, 2, 4, and 5 do not include observations in 1986 because one cannot define exit for the last year of a panel.

"Estimating Production Functions Using Inputs to Control for Unobservables"
Levinsohn and Petrin (2003)

Main idea

- Same general framework as Olley and Pakes (1996)
- Main idea: rather than use investment to control for unobserved productivity, use materials inputs.
- Two proposed benefits:
  - Investment proxy isn't valid for plants with zero investment. Zero materials inputs typically an issue in the data.
  - Investments may be "lumpy" and not respond to some productivity shocks.

Downsides of investment

- We need to drop observations with zero investment, which can lead to a substantial efficiency loss. Zero investments happen at a non-trivial rate in annual production data.
- Firms might face non-convex capital adjustment costs leading to flat regions in the $i(\omega)$ function even at positive levels of investment.
- What if investment actually happens with only partial information about productivity and then labor is set once the productivity realization is fully observed?

OP equations

- Production function:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t + \eta_t.$$

- First stage regression:

$$y_t = \beta_l l_t + \phi_t (i_t, k_t) + \eta_t$$

with $\phi_t (i_t, k_t) = \beta_0 + \beta_k k_t + \omega_t (i_t, k_t)$.

- Final regression:

$$y_t^* = y_t - \beta_l l_t = \beta_0 + \beta_k k_t + E [\omega_t | \omega_{t-1}] + \eta_t^*$$

where $\eta_t^* = \eta_t + (\omega_t - E (\omega_t | \omega_{t-1}))$.

LP equations

- Production function:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + \omega_t + \eta_t$$

- First stage regression:

$$y_t = \beta_l l_t + \phi_t\left(m_t, k_t\right) + \eta_t$$

with $\phi_t\left(m_t, k_t\right) = \beta_0 + \beta_k k_t + \beta_m m_t + \omega_t\left(m_t, k_t\right)$.

- Final regression:

$$y_t^* = y_t - \beta_l l_t = \beta_0 + \beta_k k_t + \beta_m m_t + E\left[\omega_t | \omega_{t-1}\right] + \eta_t^*$$

where $\eta_t^* = \eta_t + \left(\omega_t - E\left(\omega_t | \omega_{t-1}\right)\right)$.

Invertability

- Just as OP require $i_t(\omega_t, k_t)$ be an invertible function of productivity, LP require that input use $m_t(\omega_t, k_t)$ is an invertible function of productivity.
- LP's monotonicity result relies on easily checked properties of the production function, and some may find this more appealing than a result which relies on a Markov perfect equilibrium.
- Unobserved input price variation may be a problem for the LP invertability condition (but of course it could be for OP, too).

Checking invertability

- LP claim that
$$\text{sign}\left(\frac{\partial m}{\partial \omega}\right) = \text{sign}\left(f_{ml} f_{l\omega} - f_{ll} f_{m\omega}\right).$$
- To see this, apply the Implicit function theorem to the FOC's to get
$$\begin{pmatrix} \frac{\partial m}{\partial \omega} \\ \frac{\partial l}{\partial \omega} \end{pmatrix} = -\begin{pmatrix} f_{mm} & f_{ml} \\ f_{lm} & f_{ll} \end{pmatrix}^{-1} \begin{pmatrix} f_{m\omega} \\ f_{l\omega} \end{pmatrix}.$$
- Inverting and solving,
$$\Rightarrow \frac{\partial m}{\partial \omega} = \frac{f_{ml} f_{l\omega} - f_{ll} f_{m\omega}}{\begin{vmatrix} f_{mm} & f_{ml} \\ f_{lm} & f_{ll} \end{vmatrix}}.$$
- By the second-order condition for profit maximization, $\begin{vmatrix} f_{mm} & f_{ml} \\ f_{lm} & f_{ll} \end{vmatrix}$ must be negative semidefinite. This means it has exactly two negative eigenvalues, which means its determinant is positive. Therefore, the numerator controls the sign.

Zero inputs

TABLE 2

Per cent of non-zero observations

Industry (ISIC)	Investment	Fuels	Materials	Electricity
Food products (311)	42·7	78·0	99·8	88·3
Metals (381)	44·8	63·1	99·9	96·5
Textiles (321)	41·2	51·2	99·9	97·0
Wood products (331)	35·9	59·3	99·7	93·8

Note: in OP's industry, it was only 8% zeros.

Differences from OP

- LP use a slightly different first stage:
  - First, they estimate $E\left(z_t|k_t\right)$ for $z_t = y_t, l_t^u, l_t^s, e_t, f_t$
  - They then use no-intercept OLS to estimate:

$$\begin{aligned} y_t - E\left(y_t|k_t, m_t\right) = \quad & \beta_s\left(l_t^s - E\left(l_t^s|k_t, m_t\right)\right) \\ & + \beta_s\left(l_t^u - E\left(l_t^u|k_t, m_t\right)\right) \\ & + \beta_e\left(e_t - E\left(e_t|k_t, m_t\right)\right) \\ & + \beta_f\left(f_t - E\left(f_t|k_t, m_t\right)\right) + \eta_t \end{aligned}$$

- Second stage is similar, but they have to estimate two coefficients (β_m, β_k), so they need two moments:

$$E\left(\xi_t\begin{pmatrix} k_t \\ m_{t-1} \end{pmatrix}\right) = 0$$

TABLE 6

Comparisons across estimators P-value for H_0: $\beta_1 = \beta_2$

Comparison	Industry (ISIC code) 311	381	321	331
Levinsohn–Petrin vs.				
OLS	<0·01	0·20	0·58	0·21
Fixed effects	<0·01	<0·01	<0·01	<0·01
Instrumental variables	<0·01	0·22	0·09	<0·01
Olley–Pakes	<0·01	0·54	0·20	0·89
Levinsohn–Petrin ($i > 0$ only)	<0·01	0·02	0·27	0·93
Olley–Pakes vs.				
OLS	<0·01	0·04	0·19	0·46
Fixed effects	<0·01	<0·01	<0·01	<0·01
Instrumental variables	<0·01	<0·01	<0·01	<0·01
Levinsohn–Petrin ($i > 0$ only)	0·56	0·47	0·85	0·55
Fixed effects vs.				
OLS	<0·01	<0·01	<0·01	<0·01
Instrumental variables	<0·01	<0·01	<0·01	<0·01
No. obs.	6115	1394	1129	1032

Note: The cells in the table contain the P-value for a standard Wald test for "no differences between the (vector of) parameter estimates for estimators 1 and 2". <0·01 indicates a P-value that is less than 0·01.

"Reallocation, Firm Turnover, and Efficiency:
Selection on Productivity or Profitability"
Foster, Haltiwanger, and Syverson (2008)

Overview

- They look at some rare industries where quantity data is available, allowing them to separate physical and revenue productivity
- Findings:
  - Physical productivity is inversely correlated with price
  - Young producers charge lower prices than incumbents, meaning the literature understates entrants' productivity advantages

Measurement

- Productivity is measured as follows:

$$tfp_{it} = y_{it} - \alpha_l l_{it} - \alpha_k k_{it} - \alpha_m m_{it} - \alpha_e e_{it}$$

- Coefficients (α) are just taken from input shares by industry.
- Different measures use different output measures y:
  - TFPQ uses physical output
  - TFP uses deflated sales (using standard industry-level deflators from NBER)
  - TFPR are sales deflated by mean prices observed in their data

Correlations

TABLE 1—SUMMARY STATISTICS FOR OUTPUT, PRICE, AND PRODUCTIVITY MEASURES

Correlations								
Variables	Trad'l. output	Revenue output	Physical output	Price	Trad'l. TFP	Revenue TFP	Physical TFP	Capital
Traditional output	1.00							
Revenue output	0.99	1.00						
Physical output	0.98	0.99	1.00					
Price	−0.03	−0.03	−0.19	1.00				
Traditional TFP	0.19	0.18	0.15	0.13	1.00			
Revenue TFP	0.17	0.21	0.18	0.16	0.86	1.00		
Physical TFP	0.17	0.20	0.28	−0.54	0.64	0.75	1.00	
Capital	0.86	0.85	0.84	−0.04	0.00	−0.00	0.03	1.00
Standard deviations								
	1.03	1.03	1.05	0.18	0.21	0.22	0.26	1.14

Notes: This table shows correlations and standard deviations for plant-level variables for our pooled sample of 17,669 plant-year observations. We remove product-year fixed effects from each variable before computing the statistics. All variables are in logs. See the text for definitions of the variables.

Demand

- They estimate a demand system for each industry:

$$\ln q_{it} = \alpha_0 + \alpha_1 p_{it} + \sum_t \alpha_t YEAR_t + \alpha_2 \ln\left(INCOME_{mt}\right) + \eta_{it}$$

  where $INCOME_{mt}$ is the income in a firm's local market m

- They use the residuals from these regressions as a measure of demand shocks.

Persistence

TABLE 3—PERSISTENCE OF PRODUCTIVITY, PRICES AND DEMAND SHOCKS

	Five-year horizon		Implied one-year persistence rates	
Dependent variable	Unweighted regression	Weighted regression	Unweighted regression	Weighted regression
Traditional TFP	0.249	0.316	0.757	0.794
	(0.017)	(0.042)		
Revenue TFP	0.277	0.316	0.774	0.794
	(0.021)	(0.042)		
Physical TFP	0.312	0.358	0.792	0.814
	(0.019)	(0.049)		
Price	0.365	0.384	0.817	0.826
	(0.025)	(0.066)		
Demand shock	0.619	0.843	0.909	0.966
	(0.013)	(0.021)		

Entry and exit

TABLE 4—EVOLUTION OF REVENUE PRODUCTIVITY, PHYSICAL PRODUCTIVITY, PRICES AND DEMAND SHOCKS

	Unweighted regression		Weighted regression	
Variable	Exit dummy	Entry dummy	Exit dummy	Entry dummy
Traditional TFP	−0.0209	0.0014	−0.0164	−0.0032
	(0.0042)	(0.0040)	(0.0126)	(0.0188)
Revenue TFP	−0.0218	0.0110	−0.0197	−0.0005
	(0.0044)	(0.0042)	(0.0135)	(0.0183)
Physical TFP	−0.0186	0.0125	−0.0142	0.0383
	(0.0050)	(0.0047)	(0.0144)	(0.0177)
Price	−0.0033	−0.0015	−0.0055	−0.0388
	(0.0031)	(0.0028)	(0.0080)	(0.0141)
Demand shock	−0.3586	−0.3976	−0.5903	−0.2188
	(0.0228)	(0.0224)	(0.0968)	(0.1278)

TABLE 5—EVOLUTION OF PRODUCTIVITY, PRICE AND DEMAND WITH AGE EFFECTS

Variable	Plant age dummies: Exit	Entry	Young	Medium
Unweighted regressions				
Traditional TFP	−0.0211	0.0044	0.0074	0.0061
	(0.0042)	(0.0044)	(0.0048)	(0.0048)
Revenue TFP	−0.0220	0.0133	0.0075	0.0028
	(0.0044)	(0.0047)	(0.0051)	(0.0053)
Physical TFP	−0.0186	0.0128	0.0046	−0.0039
	(0.0050)	(0.0053)	(0.0058)	(0.0062)
Price	−0.0034	0.0005	0.0029	0.0067
	(0.0031)	(0.0034)	(0.0038)	(0.0042)
Demand shock	−0.3466	−0.5557	−0.3985	−0.3183
	(0.0227)	(0.0264)	(0.0263)	(0.0267)
Weighted regressions				
Traditional TFP	−0.0156	−0.0068	−0.0156	−0.0234
	(0.0127)	(0.0203)	(0.0171)	(0.0132)
Revenue TFP	−0.0191	−0.0038	−0.0180	−0.0165
	(0.0136)	(0.0200)	(0.0198)	(0.0131)
Physical TFP	−0.0142	0.0383	0.0056	−0.0050
	(0.0144)	(0.0186)	(0.0142)	(0.0135)
Price	−0.0049	−0.0421	−0.0236	−0.0114
	(0.0079)	(0.0147)	(0.0114)	(0.0096)
Demand shock	−0.5790	−0.2785	−0.3133	−0.3164
	(0.0972)	(0.1459)	(0.1695)	(0.1197)

TABLE 6—SELECTION ON PRODUCTIVITY OR PROFITABILITY?

Specification:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Traditional TFP	−0.073						
	(0.015)						
Revenue TFP		−0.063					
		(0.014)					
Physical TFP			−0.040			−0.062	−0.034
			(0.012)			(0.014)	(0.012)
Prices				−0.021		−0.069	
				(0.018)		(0.021)	
Demand shock					−0.047		−0.047
					(0.003)		(0.003)
Controlling for plant capital stock							
Traditional TFP	−0.069						
	(0.015)						
Revenue TFP		−0.061					
		(0.013)					
Physical TFP			−0.035			−0.059	−0.034
			(0.012)			(0.014)	(0.012)
Prices				−0.030		−0.076	
				(0.018)		(0.021)	
Demand shock					−0.030		−0.029
					(0.004)		(0.004)
Capital stock	−0.046	−0.046	−0.046	−0.046	−0.023	−0.046	−0.023
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)

"Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity"
Jan De Loecker (2011)

Overview

- Studies effects of trade liberalization on Belgian textiles producers
- Develops strategy to disentangle price and productivity effects
- We see only 2% productivity gains rather than 8% after separating out price effects.

Disappearing Quotas

TABLE I

NUMBER OF QUOTAS AND AVERAGE QUOTA LEVELS (IN MILLIONS)

	Number of Quota Protections	kg		No. of Pieces	
		No. of Quotas	Level	No. of Quotas	Level
1994	1,046	466	3.10	580	8.58
1995	936	452	3.74	484	9.50
1996	824	411	3.70	413	7.95
1997	857	413	3.73	444	9.28
1998	636	329	4.21	307	9.01
1999	642	338	4.25	304	10.53
2000	636	333	4.60	303	9.77
2001	574	298	5.41	276	11.06
2002	486	259	5.33	227	12.37
Change	−54%	−44%	72%	−60%	44%

- Meanwhile, Belgian textile prices declined by 15%

Model

- Cobb-Douglas production function:

$$Q_{it} = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} \exp\left(\omega_{it} + u_{it}\right)$$

- As usual, Q_{it} is not observed, but sales R_{it} is.
- Assumed demand system:

$$Q_{it} = Q_{st} \left(\frac{P_{it}}{P_{st}}\right)^{\eta_s} \exp\left(\xi_t\right)$$

where Q_{st} is a sectoral aggregate demand shifter

Model

- Demand is CES with monopolistic competition for each sector with markup $\left(\frac{\eta_s}{\eta_s+1}\right)$. Revenue is $R_{it} = Q_{it}P_{it}$, and at the optimal price,

$$R_{it} = Q_{it}^{(\eta_s+1)/\eta_s} Q_{st}^{-1/\eta_s} P_{st} \left(\exp\left(\xi_{it}\right)^{-1/\eta_s}\right).$$

- Expanded revenue equation (in logs):

$$\tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s Q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it}$$

  where $\tilde{r}$ is log revenue deflated by a P_{st}.

- Estimating equation:

$$\tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s Q_{st} + \delta D + \tau qr_i t + \omega_{it}^* + u_{it}$$

  where D is a vector of demand-shifting dummy variables and $qr_{it} \in [0,1]$ is a measure of exposure to quota protection.

- See paper for treatment of multi-product firms

Quotas and inversion

- $\omega_{it} = g_t\left(\omega_{i,t-1}, qr_{i,t-1}\right) + \nu_{it}$
- Inversion:
$$\omega_{it} = h_t\left(k_{it}, m_{it}, qr_{it}, q_{st}, D\right)$$
- Checking the monotonicity condition for a static input (as LP) is straightforward, but verifying the monotonicity of investment (OP) is harder.
- Estimation based on exclusion restrictions on innovation in productivity (what was ξ in previous papers but ν here:
$$E\left\{\nu_{i,t+1}\left(\beta_m, \beta_k, \beta_s, \tau, \delta\right)\begin{pmatrix} m_{it} \\ k_{i,t+1} \\ q_{st} \\ qr_{i,t+1} \\ D \end{pmatrix}\right\} = 0$$

Separation

- This framework allows for separate effects of quotas on productivity through g and demand through τ
- Identifying assumption: protection can only affect productivity with a lag (note $g_t\left(\omega_{i,t-1}, qr_{i,t-1}\right)$, while current quota protection can impact prices through residual demand.

Results

TABLE VIII

IMPACT OF TRADE LIBERALIZATION ON PRODUCTIVITY[a]

Approach	Description	Estimate	Support
I	OLS levels	−0.161* (0.021)	n.a.
II.1	Standard proxy-levels	−0.153* (0.021)	n.a.
II.2	Standard proxy-LD	−0.135* (0.030)	n.a.
III	Adjusted proxy	−0.086 (0.006)	[−0 129 −0 047]
IV	Corrected	−0.021 sd: 0.067	[−0 27 0 100]
V	Corrected LD	−0.046** (0.027)	n.a.

[a]I report standard errors in parentheses for the regressions, while I report the standard deviation (sd) of the estimated nonparametric productivity effect in my empirical model (given by $g(\cdot)$). * and ** denote significant at 5 or lower and 10 percent, respectively. LD refers to a 3 year differencing of a two-stage approach where Approach II.2 relies on standard productivity measures, as opposed to Approach V, which relies on my corrected estimates of productivity.

"Structural Identification of Production Functions"
Ackerberg, Caves, and Frazer (2006)

Overview

- ACF argue that Olley and Pakes's (1996) and Levinsohn and Petrin's (2003) approach suffer from collinearity issues.
- They propose a new approach which involves modified assumptions on the timing of input decisions and moves the identification of all coefficients of the production function to the second stage of the estimation.

LP's first stage

- Levinsohn and Petrin's first-stage regression:

$$y_{it} = \beta_l l_{it} + f_t^{-1}\left(m_{it}, k_{it}\right) + \varepsilon_{it}.$$

- LP's approach was based on the premise that materials inputs are a variable input and therefore a function of state variables:

$$m_{it} = m_t\left(\omega_{it}, k_{it}\right),$$

- They also assume that labor is a variable input (or else we would not be able to exclude it from the inversion), so

$$l_{it} = l_t\left(\omega_{it}, k_{it}\right).$$

LP's identification problem

- This means we can write:

$$y_{it} = \beta_l l_t \left(f_t^{-1} \left(m_{it}, k_{it} \right), k_{it} \right) + f_t^{-1} \left(m_{it}, k_{it} \right) + \varepsilon_{it},$$

  and since we're being nonparametric about f_t^{-1},
  it should absorb $\beta_l l_t \left(f_t^{-1} \left(m_{it}, k_{it} \right), k_{it} \right)$.

- There should be no variation in l_{it} left over to identify β_l.

Does a parametric inversion help?

- Cobb-Douglas production :

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}.$$

- FOC for materials:

$$\beta_m K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m - 1} e^{\omega_{it}} = \frac{p_m}{p_y}.$$

- Solving for ω (parametric inversion):

$$\omega_{it} = \ln\left(\frac{1}{\beta_m}\right) + \ln\left(\frac{p_m}{p_y}\right) - \beta_k k_{it} - \beta_l l_{it} + (1 - \beta_m)\, m_{it}$$

- Plugging this into the production function, the $\beta_l l_{it}$ terms cancel:

$$y_{it} = \ln\left(\frac{1}{\beta_m}\right) + \ln\left(\frac{p_m}{p_y}\right) + m_{it} + \epsilon_{it}.$$

...what identifies β_l?

Collinearity in practice and in principle

- It could be the case that l_{it} takes different values in the data for the same values of (m_{it}, k_{it}). ACF's argument is about collinearity in principle, given the assumptions of LP.
- Some potential sources of independent variation: (*Which one works?)*
  - unobserved variation in firm-specific input prices.
  - measurement error in l_{it} or m_{it}
  - optimization error in l_{it} or m_{it}

Collinearity in practice and in principle

- It could be the case that l_{it} takes different values in the data for the same values of (m_{it}, k_{it}). ACF's argument is about collinearity in principle, given the assumptions of LP.
- Some potential sources of independent variation: (*Which one works?)*
  - unobserved variation in firm-specific input prices.
  - measurement error in l_{it} or m_{it}
  - optimization error in l_{it} or m_{it}
- While optimization error in l_{it} works econometrically, it's not the most appealing assumption economically.

Another failed solution

- Note that the whole problem comes about because labor and materials are set simultaneously. This means one way to break the collinearity is to assume they are set with respect to different information sets.
- Let's try to break the informational equivalence with timing assumptions. Suppose:
  - m_{it} is set at time t
  - l_{it} is set at time $t-b$ with $0<b<1$
  - ω has Markovian in between subperiods:

$$\begin{array}{rcl} p\left(\omega_{i,t-b}|I_{i,t-1}\right) & = & p\left(\omega_{i,t-b}|\omega_{it-1}\right) \\ p\left(\omega_{it}|I_{i,t-b}\right) & = & p\left(\omega_{i,t}|\omega_{i,t-b}\right) \end{array}$$

- But this doesn't work! And neither does having m_{it} set first. *(Why?)*

An implausible solution

- Let's try again:
  - l_{it} is set at time t
  - m_{it} is set at time $t - b$ with $0 < b < 1$
  - we have a more complicated structure of productivity shocks:

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \omega_{i,t-b} + \eta_{it},$$

$$p\left(\omega_{i,t-b} | I_{i,t-1}\right) = p\left(\omega_{i,t-b} | \omega_{i,t-1}\right) ,$$

  - and there is some unobservable shock to labor prices which is realized between $t - b$ and t. This shock must be i.i.d.

- l_{it} has its own shock to respond to, creating independent variation, and the productivity inversion still works because the new shock is not a state variable.

- This works, but as ACF argue, it's rather ad-hoc and difficult to motivate.

Collinearity in Olley Pakes

- Olley Pakes's control function has the same collinearity issue, but ACF argue it can be avoided with assumptions which "might be a reasonable approximation to the true underlying process."
- Assume that l_{it} is set at $t - b$ with $0 < b < 1$. ω has a Markovian between subperiods. Then:

$$l_{it} = l_t\left(\omega_{i,t-b}, k_{it}\right),$$

  so we have variation in l_{it} which is independent of (ω_{it}, k_{it}).
- Note that even though l_{it} is set before investment i_{it}, investment won't depend on l_{it} because it is a static input. So the productivity inversion is unchanged.
- These timing assumptions cannot save LP, but they work well with OP.

ACF's alternative procedure I

- Consider value added production function:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \epsilon_{it}.$$

- ACF's procedure is based on the same timing assumption that "saves" OP: labor chosen at $t - b$, slightly earlier than when materials are chosen at t.

- Point of first stage is just to get expected output:

$$y_{it} = \Phi_t \left(m_{it}, k_{it}, l_{it} \right) + \epsilon_{it}$$

where

$$\Phi_t \left(m_{it}, k_{it}, l_{it} \right) = \beta_k k_{it} + \beta_l l_{it} + f_{it}^{-1} \left(m_{it}, k_{it}, l_{it} \right)$$

... first stage no longer recovers β_l.

ACF's alternative procedure II

- After the first stage, we have $\hat{\Phi}_{it}$, expected output.
- We can construct a measure of productivity given coeffiencts:

$$\hat{\omega}_{it}\left(\beta_k, \beta_l\right) = \hat{\Phi}_{it} - \beta_k k_{it} - \beta_l l_{it}$$

- Then, non-parametrically regressing $\hat{\omega}_{it}\left(\beta_k, \beta_l\right)$ on $\hat{\omega}_{i,t-1}\left(\beta_k, \beta_l\right)$, we can construct the innovations:

$$\hat{\xi}_{it}\left(\beta_k, \beta_l\right) = \hat{\omega}_{it}\left(\beta_k, \beta_l\right) - E\left(\hat{\omega}_{it}\left(\beta_k, \beta_l\right) | \hat{\omega}_{i,t-1}\left(\beta_k, \beta_l\right)\right)$$

ACF's alternative procedure III

- Estimation relies on the following moments:

$$T^{-1}N^{-1}\sum_t \sum_i \hat{\xi}_{it}(\beta_k, \beta_l)\begin{pmatrix} k_{it} \\ l_{i,t-1} \end{pmatrix}$$

- In the second stage, these two moments are used to estimate both β_k and β_l.
- In ACF's framework, l_{it} isn't a function of ω_{it} but of $\omega_{i,t-b}$. However, labor will still be correlated with part of the innovation in productivity, so we still need to use lagged labor in the moments.
- The moment with lagged labor is very much in the spirit of OP and LP, and they actually used it as an overidentifying restriction.

Comments

- The approach also works with an investment proxy,.
- Wooldridge (2009) proposes estimating the first and second stages together. This makes computation of standard errors easier (standard GMM formulas rather than boostrap), and it improves efficiency.

"On the Identification of Production Functions:
How Heterogeneous is Productivity?"
Gandhi, Navarro, and Rivers (2006)

Overview

- A bit like ACF's critique of OP and LP, GNR argue that past approaches suffer from non-identification.
  - The fundamental issue here is the simultaneity of flexible inputs. In a sense, we're still dealing with Marschak and Andrews (1944).
- They argue that ACF's "solution" merely moves the non-identification problem. While implementing ACF's approach with value-added production seems to avoid simultaneity, using value added production creates a misspecification problem.
- Instead, they suggest using first-order conditions from profit maximization for identification – i.e., consider the system of simultaneous equations instead of only the production function.
  - "nonparametric analogue of revenue shares directly identifying the intermediate input coefficient in a Cobb-Douglas setting"

Setup

- Consider a gross output production function (in logs):

$$y_{it} = f\left(l_{it}, k_{it}, m_{it}\right) + \omega_{it} + \varepsilon_{it}$$

- Assumptions:
  - K_{it} and L_{it} are determined at (or prior to) period $t-1$. M_{it} is determined flexibly at period t
  - Intermediate inputs can be written as $M_{it}\left(L_{jt}, K_{it}, \omega_{it}\right)$, strictly monotone in $\left(L_{it}, K_{it}\right)$.
  - ω is Markovian with evolution function $P_{\omega}\left(\omega_{it}|\omega_{i,t-1}\right)$. ε_{it} is iid and not in the information set at time t.
- These assumptions basically describe the modern framework for thinking about production function estimation. GNR claim that they are not enough to identify f.

Intuition for identification issue

- $h_t(l_{it}, k_{it}, m_{it}) = \omega_{it}$,
  $g_t(\omega_{i,t-1}) = E(\omega_{i,t}|\omega_{i,t-1})$, and
  $\xi_{it} = \omega_{it} - g_t(\omega_{i,t-1})$.

$$\begin{aligned} y_{it} &= f(l_{it}, k_{it}, m_{it}) + g_t(h_{t-1}(l_{i,t-1}, k_{i,t-1}, m_{i,t-1})) + \xi_{it} + \varepsilon_{it} \\ m_{it} &= m_t(l_{it}, k_{it}, g_t(h_t(l_{i,t-1}, k_{i,t-1}, m_{i,t-1})) + \xi_{it}) \end{aligned}$$

- The simultaneity problem comes from the fact that that m_{it} responds to ξ_{it}. But there is no instrument for m_{it} which is both valid and relevant:
  - variation in (l_{it}, k_{it}) won't help identify effect of m_{it} if we're being flexible about the functional form of f;
  - variation in $(l_{i,t-1}, k_{i,t-1}, m_{i,t-1})$ won't help if we're being flexible about the functional form of h_t.
  - the only other thing that shifts m is ξ

Using FOCs from profit maximization I

- FOC for optimal choice of intermediate inputs:

$$p_{yt} F_{M,t}\left(L_{it}, K_{it}, M_{it}\right) e^{\omega_{it}} \mathcal{E} = p_{mt}$$

  where $F_{M,t} = \frac{\partial F_t}{\partial M}$ and $\mathcal{E} = E\left(e^{\varepsilon_{it}}\right)$.

- Note: this is a *static* profit maximization assumption... is this innocent? natural?

- We can form a system of equations with the production function:

$$\begin{aligned} \ln p_{mt} &= \ln p_{yt} + \ln F_{M,t}\left(L_{it}, K_{it}, M_{it}\right) + \ln \mathcal{E} + \omega_{it} \\ y_{it} &= f_t\left(L_{it}, K_{it}, M_{it}\right) + \omega_{it} + \varepsilon_{it}. \end{aligned}$$

Using FOCs from profit maximization II

- We can form a system of equations with the production function:

$$\begin{aligned} \ln p_{mt} &= \ln p_{yt} + \ln F_{M,t}(L_{it}, K_{it}, M_{it}) + \ln \mathcal{E} + \omega_{it} \\ y_{it} &= f_t(L_{it}, K_{it}, M_{it}) + \omega_{it} + \varepsilon_{it}. \end{aligned}$$

- Differencing and adding m_{it} to both sides:

$$\ln \frac{m_{it} p_{mt}}{y_{it} p_{yt}} = s_{it}^m = \ln G_t(L_{it}, K_{it}, M_{it}) + \ln \mathcal{E} - \varepsilon_{it}$$

where s_{it}^m is materials expenditure as a share of revenue, and G_t is the elasticity of output with respect to M_{it}:

$$G_t = \frac{F_{M,t}(L_{it}, K_{it}, M_{it}) M_{it}}{F_t(L_{it}, K_{it}, M_{it})}$$

Using FOCs from profit maximization III

- The basic idea is that the input expenditure share,

$$\ln s_{it}^{m} = \ln \frac{m_{it} p_{mt}}{y_{it} p_{yt}},$$

  gives us information about how the production function depends on m_{it}.

- Notice that for a Cobb-Douglas production function,

$$\ln s_{it}^{m} = \beta_m + \varepsilon_{it},$$

  and β_m is the coefficient not identified by the ACF approach, so the idea is just to get it off the share.

Value added production

- It is fairly common in practice to estimate a value added production function:

$$y_{it} = f\left(l_{it}, k_{it}\right) + \omega_{it} + \varepsilon_{it}$$

  where y_{it} is a measure of value added rather than gross output.

- Because materials are no longer on the right hand side, this seems to avoid GNR's non-identification argument – we don't need an instrument for m if it is not an argument of the function we're trying to estimate.

- The concerns here: what is value added? and does it even make sense estimate a value added production function?
  - Most common: $y_{it} = R_{it} - m_{it}$, i.e., value added is sales net of materials expenditure
  - Structural value added (on board)

Quick Review of Dynamic Panel Data Estimation
Arellano and Bond (1991), Blundell and Bond (1998, 2000)

DP Setup

- Production function with fixed effects:

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \alpha_i + \omega_{it} + \eta_{it}$$

  where $x_t = (l_t, k_t)$, ω_{it} is the productivity term, and η_{it} is measurement error.

- Note: to justify standard fixed effects estimator, we have to assume that input choices are exogenous to ω_{it} – i.e., simultaneity is only allows with respect to the fixed effect.

- Dynamic panel data methods are an alternative to control function approaches for dealing with simultaneity.

DP Example

- Write the production function in first differences, getting rid of the fixed effect α_i:

$$\Delta y_{it} = \beta_L \Delta l_{it} + \beta_K \Delta k_{it} + \Delta \omega_{it} + \Delta \eta_{it}$$

- Suppose that
  - $l_{it} = l\left(l_{i,t-1}, k_{i,t-1}, \omega_{it}\right)$
  - $k_{it} = k\left(l_{i,t-1}, k_{i,t-1}, \omega_{it}\right)$
- If there is non-trivial serial correlation in the inputs, and no serial correlation in ω, then lagged inputs can be used as instruments.
- This DP approach can also handle some serial correlation in ω, but only if ω follows a Markov process with a linear form, like an AR1 (see ACF discussion for details).

Brief comparison

Advantages of DP methods:

- Can handle fixed effects.
- Does not rely on invertibility of input demand functions.

Disadvantages of DP methods:

- Selection bias from entry and exit.
- Potential weak instrument problems.
- Often leads to low estimates of β_l and β_k – same problem as standard fixed effects estimator killing the signal/noise ratio.
- Does not separate productivity from idiosyncratic error.
- GNR critique (simultaneity) applies: need to have quasi-fixed inputs for DP method to be identified.

Weak instruments

- Let's consider the problem with a simple production function involving only labor as an input:

$$y_{it} = \beta l_{it} + \alpha_i + \omega_{it} + \varepsilon_{it}$$

- The standard Arellano-Bond estimator would take first differences,

$$\Delta y_{it} = \beta \Delta l_{it} + \Delta \omega_{it} + \Delta \varepsilon_{it},$$

and use l_{it} as an instrument for $\Delta l_{it} = x_{it} - x_{i,t-1}$.

Weak instruments

- To avoid the problem of small-sample bias with weak instruments, we want a strong fit between Δl_{it} and $l_{i,t-2}$. We're in trouble if l_{it} is too variable or too persistent. Suppose labor inputs evolve according to the following process:

$$l_{it} = \rho l_{i,t-1} + \lambda_1 \alpha_i + \lambda_2 \omega_{it}$$

- If $\rho \approx 0$, there is little serial correlation in l_{it}, lagged values are simply not relevant predictors.
- If $\rho \approx 1$, then lagged values are relevant predictors for future levels, but we have a random walk and Δl_{it} is approximately i.i.d.
- $\Rightarrow$ it's easy to fall into a weak instruments trap here since we're hoping for an intermediate amount of persistence in the explanatory variable. Too much or too little is trouble.

Dealing with weak instruments

- An idea from Arellano and Bover (1995) and Blundell and Bond (1998) is to use another set of moments.
  - The Arellano and Bond (1991) baseline is instrumenting for differences using lagged levels:

$$E\left[x_{i,t-2}\left(\Delta\omega_{it}\Delta\varepsilon_{it}\right)\right] = 0$$

  - The new idea is instrumenting for levels using lagged differences:

$$E\left[\Delta x_{i,t-1}\left(\alpha_i + \omega_{it} + \varepsilon_{it}\right)\right] = 0$$

- The second set of moments capture more cross-sectional variation in output – note that the fixed effect typically explains most of the cross-sectional variation.
- Blundell and Bond (2000) argue that using both sets of moments leads to much more plausible parameter estimates.

	OLS Levels	Within groups	DIF t-2	DIF t-3	SYS t-2	SYS t-3
n_t	0.479	0.488	0.513	0.499	0.629	0.472
	(.029)	*(.030)*	*(.089)*	*(.101)*	*(.106)*	*(.112)*
n_{t-1}	-0.423	-0.023	0.073	-0.147	-0.092	-0.278
	(.031)	*(.034)*	*(.093)*	*(.113)*	*(.108)*	*(.120)*
k_t	0.235	0.177	0.132	0.194	0.361	0.398
	(.035)	*(.034)*	*(.118)*	*(.154)*	*(.129)*	*(.152)*
k_{t-1}	-0.212	-0.131	-0.207	-0.105	-0.326	-0.209
	(.035)	*(.025)*	*(.095)*	*(.110)*	*(.104)*	*(.119)*
y_{t-1}	0.922	0.404	0.326	0.426	0.462	0.602
	(.011)	*(.029)*	*(.052)*	*(.079)*	*(.051)*	*(.098)*
m1	-2.60	-8.89	-6.21	-4.84	-8.14	-6.53
m2	-2.06	-1.09	-1.36	-0.69	-0.59	-0.35
Sargan	-	-	.001	.073	.000	.032
Dif Sargan	-	-	-	-	.001	.102
β_n	0.538	0.488	0.583	0.515	0.773	0.479
	(.025)	*(.030)*	*(.085)*	*(.099)*	*(.093)*	*(.098)*
β_k	0.266	0.199	0.062	0.225	0.231	0.492
	(.032)	*(.033)*	*(.079)*	*(.126)*	*(.075)*	*(.074)*
ρ	0.964	0.512	0.377	0.448	0.509	0.565
	(.006)	*(.022)*	*(.049)*	*(.073)*	*(.048)*	*(.078)*
Comfac	.000	.000	.014	.711	.012	.772
CRS	.000	.000	.000	.006	.922	.641