Introduction to Production Functions

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General Motivation

- Many questions in economics require knowledge/estimation of productivity, costs, and markups as well as how these change with economic environment
- Some examples (of many): changes in competition, cost shocks, (de-)regulation, merger analysis examining effects of policies on efficiency, etc...
- Can micro empirical work deliver credible measures of these entities?

Introduction

Production-function estimates are a key input into a number of active literatures:

- Misallocation: Hsieh and Klenow (2009)
- Productivity effects of trade: Bernard and Jensen (1999), Pavcnik (2002), Amiti and Konings (2007), De Loecker (2007)
- Cost-minimization approach to estimating mark-ups: Hall (1986), De Loecker and Warzynski (2012), De Loecker, Goldberg, Khandelwal & Pavcnik (2016)
- Organizational-economics literature seeking to explain persistent productivity differentials: Gibbons and Henderson (2013), Syverson (2011).
- Energy/environment: How does CAA regulation affect productivity: Greenstone, List, and Syverson (2012)

What is a Production Function?

Commonly interested in an output function of the form

$$Y_{it} = \exp(\omega_{it}) F(L_{it}, K_{it}, M_{it})$$

where ω_{it} is a "Hicks neutral" productivity term, L_{it} is labor, M_{it} is materials/electricity/intermediate inputs

Consider Cobb-Douglas functional form for F (ignoring subscripts)

$$Y = AL^{\alpha} K^{\beta} M^{\gamma}$$

What does a production function tell us?

- Output elasticities: α, β, γ
    - With constant returns to scale + no markups = cost share
- Total factor productivity: A
- Returns to scale: $\alpha + \beta + \gamma \gtreqless 1$

What is a Production Function?

Production Function Terminology

- Gross Output Production Function: $Y = AL^{\alpha}K^{\beta}M^{\gamma}$
- Value Added Production Function $(Y - M) = AL^{\alpha'}K^{\beta'}$

Different Functional Forms: Two most commonly used

1. Cobb Douglas: [2 factor KL, 3 factor KLM, 4 factor KLEM]
2. Translog: 3 Factor example

$$\begin{aligned}\ln(Y) = \ln(A) &+ a_L \ln(L) + a_K \ln(K) + a_M \ln(M) + \\ & b_{LL} \ln(L)^2 + b_{KK} \ln(K)^2 + b_{MM} \ln(M)^2 + \\ & b_{LK} \ln(L)\ln(K) + b_{LM} \ln(L)\ln(M) + b_{KM} \ln(K)\ln(M)\end{aligned}$$

Data Issues #1

Where does data come from typically?:

- More and more, empirical work on production, productivity, and industry dynamics relies on national surveys of manufacturing establishments like the Census of Manufactures and Annual Survey of Manufacturing in the US.
- Researchers have also used plant-level data from Chile, China, Columbia, Denmark, France, India. Some barriers to access.
- Firm-level data sets (e.g., Compustat) can be easier to access, but typically lack establishment-level info, less detail about inputs/outputs, and introduce sample selection issues
- Some researchers have acquired data sets with detailed cost information from specific firms (e.g. Benkard (2000) on learning by doing).

Data Issues #2

Quantities versus expenditures/revenues

- Production function is a statement about quantities (units of input/output)
- Most often observe revenues / expenditures
- Translate revenues / expenditures to quantities using price indices ($P \times Q/\tilde{P}$)
- Can lead to various biases in estimation [More Later]

Capital Stocks

- Rarely directly observed
- Imputed using observed investment + depreciation (i.e. "perpetual inventory method")

Other Issues Re: Data: Multi-product production, Quality Differentiation

- Typically only observe inputs for overall production (i.e. not product specific)

Empirical/Estimation Issues

Analysis is often at 4-digit SIC code level

- Common production technology across firms within an industry

Two Main Issues + Some Others

1. "Transmission Bias" (i.e. Simultaneity)
   - Labor, capital and material choices depend on unobserved productivity
   - For example, firms with high productivity draws will hire more workers
   - Dates back to Marshak and Andrews (1944)

2. Selection: Productive firms are less likely to exit
   - Age of firm is often positively correlated with productivity
   - Large degree of entry and exit correlated with firm outcomes (Dunne, Roberts and Samuelson, 1988)

3. Others: measurement error, specification, multicollinearity
   - Functional form: Cobb-Douglas, CES, Translog, Leontief, constant vs random coefficients?
   - Multicollinearity: Some inputs may be highly correlated if they are highly complementary.

Estimation: OLS

Let's use a simple Cobb-Douglas production function as example

$$Y_t = A_t K_t^{\alpha} L_t^{\beta}$$

Log transformation

$$\ln Y_t = \alpha \ln K_t + \beta \ln L_t + \ln A_t$$

- Run OLS: output on input choices, residual = productivity

Challenges

- Generally, we should expect input use (and output) to respond to A_t.
- For example, if capital is set at $t-1$ and labor can be adjusted at t, we should expect labor to respond to the current realization of productivity.
- Endogeneity / omitted variable bias

Estimation: Fixed Effects

Fixed Effects

- Another potential solution to the simultaneity problem is to assume $A_{it} = \mu_i + \epsilon_{it}$ and that ϵ_{it} is uncorrelated with input decisions.

Challenges

- Measurement Error / Attenuation: One problem with this (and fixed effects more generally) is that they kill the signal-to-noise ratio.
  - Capital typically has little variation within firm + lots of measurement error $\Rightarrow$ significant downward bias in capital coefficient when using FE

- Time varying productivity: Productivity may not be time invariant, and often we're interested in identifying how it responds to some change in the environment.

Estimation: Other Methods

Instrumental Variables:

- Seems like obvious solution to endogeneity concerns
- Challenges - hard to find exogenous shifters in input demand
  - Some have proposed input prices, but typically not observed at establishment level, and establishment level variation probably endogenous.

Control Function Approaches: e.g., Olley-Pakes, ACF [more later]

- Add in control function for productivity to "solve" simultaneity issue
- Currently the preferred "frontier" approach
- Relies on fairly strong assumptions about productivity DGP (markov) + ability to control for productivity using observables + timing assumptions

Dynamic Panel Methods [more later]

- Often run into weak / poor instrument problem
- Higher data demands due to lagged (differenced) instruments
- Strong identifying assumptions

"Estimation": Index Methods

Wow, all those methods seem fraught with peril.

What if I don't want to make all of those difficult to verify assumptions?

Productivity "Index" Methods

- Cobb-Douglas Production + CRS + no markups
- Output elasticities = cost/revenue shares

$$\ln A_t = \ln Y_t - \alpha \ln K_t - \beta \ln \; L_t$$

- Where $\beta = \frac{\text{labor expenditures}}{\text{revenue}}$

See e.g., Syverson JEL or Foster, Haltiwanger, Syverson (2008)

Control functions: Olley-Pakes (1996)

Olley-Pakes (1996)

- 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.

Control Functions

- Main idea: model choice of inputs as a function of unobserved term.
- Include as a control to "break" simultaneity/endogeneity issue

OP assumptions

Basic Setup: Cobb-Douglas in Capital (K) and Labor (L)

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

Assumption 1: ω_{it} follows exogenous first order Markov process,

$$p(\omega_{it+1}|\mathcal{I}_{it}) = p(\omega_{it+1}|\omega_{it})$$

Assumption 2: Capital at t determined by investment at time $t-1$,

$$k_t = (1-\delta)k_{it-1} + i_{it-1}$$

Assumption 3: Investment is a function of ω and other observed variables

$$i_{it} = I_t(k_{it}, \omega_{it}),$$

and is strictly increasing in ω_{it}

Assumption 4: Labor variable and non-dynamic, i.e. chosen each t, current choice has no effect on future (can be relaxed)

Productivity Inversion

This is the key "trick" in OP

- In a technical paper, Pakes (1994) shows that optimal investment $i_t(\omega_t, k_t)$ is monotonically increasing in ω_t, provided $i_t > 0$.
- Given monotonicity, optimal investment can be inverted for productivity: $\omega_{it} = h_t(i_{it}, k_{it})$.
- We're going to talk more about the $i_t > 0$ with Levinsohn and Petrin (2003).

Model is estimated in two stages

First Stage

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

- Substituting in the inversion function,

$$y_{it} = \beta_l l_{it} + \phi_t(i_{it}, k_{it}) + \epsilon_{it} \tag{1}$$

  where

$$\phi_t(i_{it}, k_{it}) = \beta_k k_{it} + h_t(i_{it}, k_{it})$$

- We can estimate this equation using a semiparametric regression. This may identify β_l, but not the other coefficients.
  - Useful to think of h_t as polynomial function of inputs (i.e. estimate equation (1) via OLS)
- 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.

Second Stage: Identifying β_k

- Lets first think about how to do this without worrying about exit. Define

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

so that

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

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

- We can write out a second stage regression equation:

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

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

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

Second Stage: Identifying β_k

- Second stage regression equation:

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

- 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), (nonparametrically) estimate g conditional on those value of (β_k), and then back out $\xi_{i,t}(\beta_k)$.
  - Search over (β_k) to minimize sum of squares of $\xi_{i,t}(\beta_k)$.

- Conditional on values of (β_k), we can construct an estimate of $\omega_t = \phi_t - \beta_k k_t$
  - Note that $E(\xi_{i,t} l_{i,t}) \neq 0$ is what creates the need for the first stage.

Olley-Pakes - Additional Details

What happens with non-random entry / exit?

- Selection might affect estimates of output elasticities
- OP add in a second control function that predicts probability of exit, conditional on some observables.

Productivity Decomposition

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

$$\begin{aligned}
\omega_t =& \sum_{i=1}^{N_t} (\bar{s}_t + \Delta s_{it})(\bar{\omega}_t + \Delta\omega_{it}) \\
=& N_t \bar{s}_t \bar{\omega}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta\omega_{it} \\
=& \bar{\omega}_t + \sum_{i=1}^{N_t} \Delta s_{it} \Delta\omega_{it}
\end{aligned}$$

  where $\bar{\omega}_t$ is unweighted mean productivity
- Thus, aggregate productivity decomposes into an unweighted mean and a covariance term (covariance between productivity and market share)
- Many other useful decompositions (see e.g. Melitz and Polanec (2015))

Discussion: Olley-Pakes

Important paper

- Large literature follows
- Estimation is straightforward (opreg in STATA)
- Analysis of an important issue
- Uses widely available variables

Issues

- Relies strongly on single index restriction of productivity (i.e. to use CF)
- Measurement errors in investment is problematic
- Cannot accomodate zero investment or non-monotonic investment

What if deregulation or other market forces affect product quality? Markups?

Unobserved output and input prices

- Rewrite production function (1) with vector of inputs:

$$y_{it} = x_{it}'\beta + \psi_{it} + \epsilon_{it}$$

$$r_{it} = \underbrace{y_{it} + p_{it}}_{\text{revenue } = p \times q}, \mathbf{e}_{it} = \underbrace{\mathbf{x}_{it} + \mathbf{w}_{it}}_{\text{expenditures } = \text{ quantity*cost}}$$

- Typically only <u>sectoral</u> price indices are available. Suppose:

$$p_{it} = \overline{p}_t + \breve{p}_{it} \quad \mathbf{w}_{it} = \overline{\mathbf{w}}_{\mathbf{t}} + \breve{\mathbf{w}}_{it}$$

- Combining (2)-(4):

$$\underbrace{\{r_{it} - \bar{p}_t\}}_{\text{deflated revenues}} = \underbrace{\{\mathbf{e}_{it} - \bar{\mathbf{w}}_t\}'}_{\text{deflated expend}} \beta + \{\breve{p}_{it} - \breve{\mathbf{w}}_{it}'\beta + \psi_{it} + \epsilon_{it}\}$$

- $\mathbf{e}_{it}, \breve{p}_{it}$ correlated $\Rightarrow$ "output price bias"
- $\mathbf{e}_{it}, \breve{\mathbf{w}}_{it}$ correlated $\Rightarrow$ "input price bias"

Unobserved output and input prices (cont.)

- Further discussion in Katayama, Lu and Tybout (2009), De Loecker and Goldberg (2014).
- Observing $\breve{p}_{it}$ (i.e. plant specific prices and/or output quantities) solves output price bias.
  - Yields TFP-Q, estimated by Foster, Haltiwanger and Syverson (2008) for homogeneous-good industries: block ice, plywood, raw cane sugar...
- Observing $\breve{\mathbf{w}}_{it}$ (i.e. plant specific input prices) solves input price bias.
  - Rarely observed (Colombian data)
  - Other control function solutions (De Loecker, Goldberg, Khandelwal, Pavcnik (2015))

Olley-Pakes: Critiques and extensions

- Levinsohn, Petrin (2003): investment often zero, so use other inputs instead of investment to form control function
- Ackerberg et al. 2016: control function often collinear with l_{it} — for it not to be must be firm specific unobervables affecting l_{it} (but not investment / other input or else demand not invertible and cannot form control function)
- Gandhi et al. 2009: relax scalar unobservable in investment / other input demand
- Wooldridge 2009: more efficient OP estimation (GMM as opposed to 2-step)

Levinsohn, Petrin (2003)

- 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:
  1. Investment proxy isn't valid for plants with zero investment. Zero materials inputs typically an issue in the data.
  2. Investments may be "lumpy" and not respond to some productivity shocks.

Levinsohn, Petrin (2003): Critiques

Solve one issue (investment $= 0$), but introduce another...

Ackerberg, Caves, Frazer

- ACF argue that Olley and Pakes (1996) and Levinsohn and Petrin (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:

$$y_{it} = \beta_l l_{it} + f_t^{-1}(m_{it}, k_{it}) + \epsilon_{it}$$

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

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

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

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

LP's identification problem

- This means we can write:

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

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

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

Ackerberg Caves and Frazer (2015): Production Function Estimation

Olley-Pakes/ACF: "1st Stage" Estimation

$$y_{it} = \theta(l_{it}, k_{it}, m_{it}) + \epsilon_{it}$$

Get predicted values $\hat{\theta}_{it}$, and now know productivity up to a vector of output elasticities

$$\omega_{it}(\beta) = \hat{\theta}_{it} - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it}$$

"2nd Stage" Solution: use law of motion for productivity to construct moments

$$\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}$$

Current period productivity "innovation" should be orthogonal to lagged input choices for variable inputs (i.e. materials) and orthogonal to current period input choices for dynamic inputs (i.e. capital... because chosen in previous period)

$$E\left(\xi_{it}(\beta)\begin{pmatrix} k_{it} \\ l_{it} \\ m_{it-1} \end{pmatrix}\right) = 0$$

Estimate using GMM

ACF: Empirical example

- Chilean plant level data
- Compare OLS, FE, LP, ACF, and dynamic panel estimators
- LP and ACF using three different inputs (materials, electricity, fuel) for control function
- Results:
  - 311=food, 321=textiles, 331=wood, 381=metal
  - Expected biases in OLS and FE
  - ACF and LP significantly different
  - ACF less sensitive to which input used for control function
  - Dynamic panel closer to ACF than LP, but still significant differences

TABLE 1

	Industry 311					
	Capital		Labor		Returns to Scale	
	Estimate	SE	Estimate	SE	Estimate	SE
OLS	0.336	0.025	1.080	0.042	1.416	0.026
FE	0.081	0.038	0.719	0.055	0.800	0.066
ACF – M	0.371	0.037	0.842	0.048	1.212	0.034
ACF – E	0.379	0.031	0.865	0.047	1.244	0.032
ACF – F	0.395	0.033	0.884	0.046	1.279	0.028
LP – M	0.455	0.038	0.676	0.037	1.131	0.035
LP – E	0.446	0.032	0.764	0.040	1.210	0.034
LP – F	0.410	0.032	0.942	0.040	1.352	0.036
DP	0.391	0.026	0.987	0.043	1.378	0.028
	Industry 321					
	Capital		Labor		Returns to Scale	
	Estimate	SE	Estimate	SE	Estimate	SE
OLS	0.256	0.035	0.953	0.056	1.210	0.034
FE	0.204	0.068	0.724	0.087	0.927	0.108
ACF – M	0.242	0.041	0.893	0.063	1.135	0.040
ACF – E	0.272	0.037	0.832	0.060	1.104	0.039
ACF – F	0.272	0.038	0.873	0.061	1.145	0.040
LP – M	0.320	0.037	0.775	0.059	1.094	0.049
LP – E	0.241	0.037	0.978	0.065	1.219	0.047
LP – F	0.254	0.039	1.008	0.062	1.262	0.048
DP	0.320	0.042	0.837	0.064	1.157	0.041
	Industry 331					
	Capital		Labor		Returns to Scale	
	Estimate	SE	Estimate	SE	Estimate	SE
OLS	0.236	0.047	1.038	0.074	1.274	0.052
FE	-0.028	0.103	0.897	0.095	0.869	0.136
ACF – M	0.196	0.064	0.923	0.085	1.119	0.076
ACF – E	0.195	0.065	0.897	0.088	1.092	0.073

Productivity Seems Important but Difficult to Estimate

Various approaches (can be a polarizing literature):

High Level Strategies

- Ignore the problems.
- Focus on one specific industry where we have very good data
  - Electricity, cement, fracking, oil drilling, etc...
- Focus on other variables: labor productivity, prices , employment.

Addressing Output/Input Price Biases

- Use undeflated sales, expenditures, think of TFP as measure of profitability, not technical efficiency.
- Focus on homogenous-good industries: Foster et al. (2008), Ganapati, Shapiro, and Walker (2016)
- Model markups directly and embed demand system into production function (e.g. de Loecker (2011))

Broad advice: worth checking that conclusions are not sensitive to approach

Application: Greenstone, List, and Syverson (2012)

What is the question, and why is it interesting?

- What are the economic costs of environmental policy?

Why is the existing literature crappy, nonexistent, and/or unresolved

- While there has been some work on this topic, it has been somewhat ad hoc without a clear connection to economic costs and/or welfare (e.g. employment effects, plant re-location, etc...)

What are the authors going to do to solve it?

- Combine detailed plant-level data from Census and Annual Survey of Manufacturers with variation in regulatory stringency induced by United States Clean Air Act
- Plant-level productivity index measures used in diff-in-diff framework

Clean Air Act (CAA) - Revisited

The largest environmental program in the United States

- First enacted in 1963 with major revisions in 1970, 1977, and 1990.
- National Ambient Air Quality Standards (NAAQS) for certain criteria air pollutants (CO, O_3, NO_2, SO_2, PM)
- Administered at the County$\times$Pollutant$\times$Year level
- Areas that exceed the EPA pollution threshold in a given year are designated as "Nonattainment"

Conceptual Framework

Production Technology

$$Q = A\tilde{L}^{\alpha}\tilde{K}^{1-\alpha}$$

where Q is output, A is productivity ("Hick's Neutral"), and $\tilde{L}$ and $\tilde{K}$ are labor + capital inputs

- $\tilde{L}$ and $\tilde{K}$ are "production effective" labor + capital
- Differ from observed labor L and capital K

$$\tilde{L} = \lambda_L L \text{ and } \tilde{K} = \lambda_k K$$

- Idea that regulation increases use of inputs not directly used for producing output (e.g. scrubber or environmental compliance officer)

Conceptual Framework

More stringent environmental regulation can be interpreted as a decrease in λ_L and/or λ_k.

Plugging into production function

$$Q = A(\lambda_L L)^{\alpha}(\lambda_K K)^{1-\alpha}$$

$$TFP = \frac{Q}{L^{\alpha}K^{1-\alpha}} = \frac{A(\lambda_L L)^{\alpha}(\lambda_K K)^{1-\alpha}}{L^{\alpha}K^{1-\alpha}} = A\lambda_L^{\alpha}\lambda_k^{1-\alpha}$$

Decreases in λ_L and/or λ_k driven compliance-related inputs are inward shifters of the plant's production function.

- i.e. amount of output per unit of observed input (TFP) decreases.

Data - Who are Polluting Firms?

Not entirely obvious how to model "polluting firms" in this context

- Here: somewhat ad hoc approach based on EPA classification of "heavy emitter" industries in the 1970's. Implications?
- Other approaches: (i) plant-level CAA operating permits, (ii) plant-level emissions inventories, etc...

Empirical Specification

$$(1) \qquad TFP_{it} = \sum_p \{\beta_p I[nocaaa_{cpt}] + \delta_p I[pollind_{ip}] + \gamma_p I[nocaaa_{cpt}] I[pollind_{ip}]\} + X_{it}\Phi + \eta_i + \varepsilon_{it},$$

- i.e. what is the effect of being a polluting plant (for pollutant p) in a nonattainment county?
- Plant specific FE isolate identifying variation to come from within plant, before/after change in nonattainment status

Baseline Results

Table 3: TFP Effects of Nonattainment, Core Specifications

Pollutant	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Any	-0.024**		-0.023**		-0.026**		-0.044**	
	(0.003)		(0.003)		(0.006)		(0.007)	
O_3		-0.018**		-0.018**		-0.022**		-0.057**
		(0.004)		(0.004)		(0.007)		(0.008)
TSPs		0.010**		0.009**		-0.013*		-0.011
		(0.004)		(0.004)		(0.007)		(0.008)
SO_2		0.000		-0.002		-0.016		-0.021*
		(0.006)		(0.006)		(0.010)		(0.011)
CO		-0.021**		-0.024**		0.017*		0.022**
		(0.005)		(0.005)		(0.009)		(0.010)
4-Digit SIC x Year	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Census Div x Year	No	No	Yes	Yes	No	No	Yes	Yes
2-Digit SIC x Period	No	No	No	No	Yes	Yes	No	No
Census Div x Period	No	No	No	No	Yes	Yes	No	No
Plant	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.766	0.766	0.801	0.801	0.887	0.887	0.887	0.887

Underestimate / Overestimates

Some concerns:

- Price effects?
- Entry/Exit
- Measurement error / SUTVA

Some Solutions

- Examine price effects in an industry with prices: ready-mixed concrete
    - Homogenous product with reported quantity data $\Rightarrow$ unit prices
- Examine entry/exit directly and do some selection corrections to account for non-random exit
- Examine sensitivity of results to arbitrary polluter definitions

Output Price Bias

Table 7: TFP and Price Effects of Nonattainment, Ready-Mixed Concrete Plants

	Dependent Variable		
Pollutant	Revenue TFP	ln(price)	Physical Quantity TFP
Nonattainment for O_3, TSPs, and/or SO_2	-0.006 (0.019)	0.027** (0.010)	-0.033 (0.021)
R^2	0.635	0.660	0.649

Extend intuition to other industries using average TFP-price relationship from NBER-CES database

- Every 1% increase in industry TFP, industry price falls by roughly 0.35%
- Average effect of nonattainment on TFP-R $\approx$ 2.6% $\Rightarrow$ implied impact on true technical efficiency is then actually $2.6/(0.65) = 4\%$
  - Identity: $\Delta TFP_{rev} = \Delta TFP_q + \Delta ln(p)$.
  - Implication: $\Delta TFP_{rev} = \Delta TFP_q - 0.35 * \Delta TFP_q \Rightarrow \Delta TFP_q = \Delta TFP_{rev}/0.65$

Welfare Analysis

Assuming firms are price takers, can calculate reduction in welfare using productivity estimates

- \$423 billion in counterfactual output $\$412.5B/(1 - 0.026)) \Rightarrow \$11$ billion annually
- Number gets bigger when including price + selection effects

Questions, issues, interpretation?

- Would be really nice to know some more about price effects (and/or markups)
- Very little discussion / analysis of mechanisms
  - e.g., fixed versus marginal costs
  - Decomposition (e.g. OP market share reallocation vs. avg productivity)
- Lots of unexplored heterogeneity
- Endogeneity of nonattainment designations

De Loecker and Collard Wexler (2015)

What is the question, and why is it interesting?

- To what extent are productivity gains in steel driven by technological innovation versus reallocation to more productive plants?

Why is the existing literature crappy, nonexistent, and/or unresolved?

- We know relatively little about underlying drivers of productivity
- Identification challenges and data limitations

What are the authors going to do to solve it?

- Detailed exploration of steel production using Census of Manufacturers, combined with information on technology adoption
- Estimate production functions + engage in various productivity decompositions

De Loecker and Collard Wexler (2015)

Things I like about this paper

- Shows how much information we can squeeze out of a production function
  - Technical efficiency measures
  - Productivity decompositions
  - Markups / welfare analysis, etc...
- Pushes the Census data further than most (e.g. "product + materials trailer", observed technological adoption, price data on outputs and inputs, etc...)

Things I am less enthused about:

- Not really a sharp-null hypothesis
- That's ok, but these papers can be difficult to write/sell.

Data and Estimation

Output and input prices

- Use data from BLS Producer Price Indices + information on material input usage (product level) and output (product level) to construct plant-level price indices for inputs/outputs

Production Function

- Cobb-Douglas in labor, materials, and capital
- Modeled/estimated separately for mini-mills versus vertically integrated production
- ACF estimation with augmented productivity process

Production Function Results

	Input and Output Price Deflators		No Plant-Level Output Price Deflator		No Plant-Level Input Price Deflator	
	GMM	OLS	GMM	OLS	GMM	OLS
	I	II	III	IV	V	VI
Material	0.680	0.631	0.650	0.610	0.680	0.631
	[0.65 0.73]	*[0.58 0.69]*	*[0.62 0.70]*	*[0.52 0.67]*	*[0.64 0.73]*	*[0.58 0.69]*
Labor	0.274	0.327	0.282	0.332	0.273	0.327
	[0.24 0.31]	*[0.28 0.37]*	*[0.24 0.32]*	*[0.29 0.38]*	*[0.24 0.31]*	*[0.28 0.37]*
Capital	0.079	0.050	0.082	0.051	0.082	0.050
	[0.04 0.11]	*[-0.01 0.10]*	*[0.05 0.11]*	*[-0.01 0.10]*	*[0.05 0.11]*	*[-0.01 0.10]*
VI premium	-0.075	-0.018	-0.038	0.013	-0.076	-0.018
	[-0.12 -0.04]	*[-0.04 0.00]*	*[-0.08 0.00]*	*[-0.01 0.03]*	*[-0.12 -0.04]*	*[-0.04 0.00]*

VI premium comes from auxiliary regression of productivity on VI dummy

- Other explanations for minimill productivity premium?
- Management, geography, trade, unions...

Static Decomposition

Recall OP decomposition of productivity into average productivity versus output reallocation to more productive plants

Extend that logic to examine how aggregate productivity driven by:

1. Changes in average productivity of MM and VI plants
2. Changes in covariance between output and productivity (separately for MM, VI)
3. Reallocation across technologies (i.e. between MM and VI)

Static Decomposion Results

Table 7: Static Decompositions of Productivity Growth (Change 1963-2002)

Aggregate TFP $\Delta\Omega$	22.1%	
Olley-Pakes Decomposition:		
Unweighted Average: $\Delta\overline{\omega}$	15.7% (0.71)	
Covariance: $\Delta\Gamma^{OP}$	6.4% (0.29)	
Between Decomposition:		
Unweighted Average: $\Delta\overline{\Omega}$	17.0 % (0.77)	
Between Covariance: $\Delta\Gamma^{B}$	5.1 % (0.23)	
Within Decomposition:	Minimills	Integrated
Aggregate TFP: $\Delta\Omega(\psi)$	9.6%	24.3%
Unweighted Average: $\Delta\overline{\omega}(\psi)$	5.4% (0.55)	18.4% (0.83)
Within Covariance: $\Delta\Gamma^{OP}(\psi)$	4.4% (0.45)	3.7% (0.17)

- Average increase in plant productivity (15.7) vs. reallocation (6.4)
- Reallocation between VI and MM led to 5.1 increase
- Minimills increased by 10 whereas VI increased by 24
  - Higher increase in average plant productivity in VI (18.4 $\Rightarrow$ 83 percent)

Welfare Analysis

By how much did CS increase with introduction of minimills?

- Need to know ΔQ and ΔP

Back of the envelope:

1. Have information on price changes from PPI (need to attribute some fraction of that to minimills $\approx$ 51 percent)
2. Have information on revenues / output in 1963
3. Use various demand elasticities (from other papers or markup inversion)
4. Calculate area of trapezoid

Table B.9: Welfare effects under various demand elasticities

	$\epsilon = -0.6$	$\epsilon = -3.5$	$\epsilon = -1$
60% Fall in Prices Due to Minimills			
Change CS	9.3 Billion $	11.2 Billion $	9.5 Billion $
Share Change CS	13%	16%	13%
100% Fall in Prices Due to Minimills			
Change CS (All)	17 Billion $	23 Billion $	18 Billion $
Share Change CS (All)	24 %	33 %	25 %

Note: The different elasticities of demand are based on 1) an empirical study of U.S. steel by Maasoumi et al. (2002) , 2) the implied (averaged across time and plants) elasticity of demand from our markup estimates, and 3) an unit-elastic demand curve. Throughout our calculations we assume a linear demand curve. The consumer

What Else Can We Do With Production Functions?

Estimating Markups and Marginal Costs from Production Functions

- Assuming firms are cost minimizing, we can back out plant-level markups from production functions
- With price data, can recover marginal costs
- Can then explore how price, marginal cost, and markups respond to changes in the economic environment

Recent examples:

- De Loecker and Warynski (2012), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), Ganapati, Shapiro, and Walker (2016)

Methodology - Markups

Some Intuition: How do we get markups from output elasticities of the production function?

$$Y = AK^{\alpha}L^{\beta}$$

- F.O.C. of firm relates output elasticity of a variable input (e.g. materials) to revenue share of input and markup (Hall 1988; De Loecker, Warzynski 2012)
- Under imperfect competition, input growth is associated with disproportional output/revenue growth
- Deviation between output elasticity of input and revenue growth identifies markup

Methodology - Markups

Markup Mechanics: Quick illustration/derivation

- General production function with hicks-neutral productivity:

$$Q = F(\mathbf{V}, \mathbf{K})\Omega$$

V: variable input (materials); **K**: dynamic input (capital, labor); Ω: TFP

- Firm minimizes cost of variable input(s), conditioning on dynamic inputs
- Lagrangian:

$$L(\mathbf{V}, \mathbf{K}, \lambda) = \sum_{v=1}^{V} P^V V^V + \mathbf{rK} + \lambda[Q - Q(\mathbf{V}, \mathbf{K}, \Omega)]$$

Markups

- The marginal cost of production (for a given level of output) is λ
  - i.e. since $\frac{\partial L}{\partial Q} = \lambda$
- FOC for variable input (e.g. materials):

$$\frac{\partial L}{\partial V^V} = P^V - \lambda \frac{\partial Q(.)}{\partial V^v} = 0$$

Markups

- The marginal cost of production (for a given level of output) is λ
  - i.e. since $\frac{\partial L}{\partial Q} = \lambda$
- Take FOCs:

$$\frac{\partial L}{\partial V^V} = P^V - \lambda \frac{\partial Q(.)}{\partial V^v} = 0$$

$$\frac{\partial Q(.)}{\partial V^v} \frac{V^v}{Q} = \frac{1}{\lambda} \frac{P^v V^v}{Q}$$

Markups

- The marginal cost of production (for a given level of output) is λ
  - i.e. since $\frac{\partial L}{\partial Q} = \lambda$
- Take FOCs:

$$\frac{\partial L}{\partial V^V} = P^V - \lambda \frac{\partial Q(.)}{\partial V^v} = 0$$

$$\frac{\partial Q(.)}{\partial V^v} \frac{V^v}{Q} = \frac{1}{\lambda} \frac{P^v V^v}{Q}$$

$$\underbrace{\frac{\partial Q(.)}{\partial V^v} \frac{V^v}{Q}}_{\text{output elasticity}} = \underbrace{\frac{P}{\lambda}}_{\text{Markup}} \times \underbrace{\frac{P^v V^v}{PQ}}_{\substack{\text{Input's share} \\ \text{of revenue}}}$$

- Markup identified using output elasticity [estimate] and revenue share [data]
- If we observe prices in the data, we can calculate marginal costs from estimated markups: **MC = Price - Markup**

Other ways to estimate markups/marginal costs: "Demand Side Approaches"

Demand Side Approach to Markups: "estimating costs without cost data"

1. Assume a utility function. Use it to estimate price elasticities of demand (e.g., BLP)
2. Assume a particular market structure and behavior (i.e. pricing rule)
3. The assumptions in 1. and 2. imply particular markups
4. Once we know markups, marginal costs are identified based on the identity:

$$\ln MC = \ln P - \ln MU$$

Demand Side: Advantages and Disadvantages

Advantages

- Full (partial equilibrium) modelling of the market
- Permits counterfactual analysis
- Mechanisms clear

Disadvantages

- Results depend on assumptions.
- Therefore, most commonly applied to case studies where institutional setup can inform assumptions
- Emerging consensus: approach does well in cross-section.
  - Less successful in explaining time series of prices and markups as well a price adjustment to shocks.

Demand versus Production Function Approach to Markup Estimation

Production Function Approach to Markups

1. Arguably fewer assumptions
2. Applicable to a broad set of industries
3. Can be implemented using manufacturing firm surveys $\rightarrow$ increasingly available

Recent paper comparing/contrasting estimates from different approaches

- de Loecker and Scott (2017): Beer industry

Application: Ganapati, Shapiro, and Walker (2017)

Research Question: How do externality correcting taxes affect consumers and producers (and ultimately welfare) in imperfectly competitive product markets?

- Economic Incidence: Relative change in consumer versus producer surplus
- Welfare: Do corrective taxes $\downarrow\uparrow$ welfare in economies with market power?

Why Should We Care?

- Implications of carbon taxation? Prices, profits, and welfare?
- Market power especially important for environmental taxes.
  - Dirtiest industries typically concentrated (e.g., oil refining, cement, steel)
- Very little empirical evidence on welfare/incidence of input taxation in context of imperfect competition

Empirics: Welfare, Incidence, and Market Structure

To estimate Δwelfare/incidence of a tax, need to know:

- supply curve / marginal costs
- demand curve / preferences
- market structure

How to make empirical progress?

- Reduce dimensionality of problem to estimating a set of "reduced-form" parameters (e.g., cost pass-through)
  - As opposed to specifying preferences, market structure, supply curves, etc...
- Derive sufficient statistics expressions for welfare/incidence of input taxes under imperfect competition
  - Extend recent work exploring incidence of output taxes under imperfect competition (Weyl and Fabinger 2013) to consider input taxation

Incidence: Theory

Goal: Incidence of input taxes for imperfectly competitive industries

- Recent theory of incidence in context of imperfect competition applies to output taxes (e.g., Weyl and Fabinger 2013)
- Incidence of output taxes can differ from input taxes because firms can substitute across different inputs

Extend Weyl and Fabinger (2013): Derive a partial equilibrium expression for incidence as a function of four statistics that we estimate

1. pass-through rate
2. markup
3. demand elasticity
4. cost-shift rate

Incidence results apply to arbitrary forms of imperfect competition

- Does not require us to assume that firms engage in Bertrand, Cournot, etc.

Incidence and Pass-Through: Basic Theory

Definitions: Incidence and pass-through rate of tax t

Incidence, $I \equiv \frac{dCS/dt}{dPS/dt}$ Pass-through rate, $\rho \equiv \frac{dp}{dt} = \frac{1}{1+\frac{\epsilon_D}{\epsilon_S}}$

Standard incidence result under perfect competition and monopoly

$$I^{Competitive} = \frac{\rho}{1-\rho} \qquad I^{Monopoly} = \rho$$

Intuition [perfect competition] $\Rightarrow$ envelope theorem

- Marginal increase in t decreases CS by Q^* times change in consumer prices, ρ
- Marginal increase in t decreases PS by Q^* change in producer margins, $1-\rho$

Pass-through: sufficient statistic for incidence under perfect comp. and monopoly

▸ Monopoly ▸ Demand Forms

Incidence and Pass-Through: Oligopoly

In general, incidence depends on both pass-through and market structure

- For simplicity, symmetric firms but compete in arbitrary market structure

Define θ as measure of imperfect competition:

- $\theta = 0$ is Perfect Competition; $\theta = 1$ is Monopoly

$$\theta \equiv \underbrace{\left(\frac{p - mc}{p}\right)}_{\text{i.e. Lerner index, } L} \times \epsilon_D$$

where ϵ_D is the elasticity of demand and L is Lerner Index / markup

General Incidence Formula

$$I^{Oligopoly} = \frac{\rho}{1 - (1 - \theta)\rho} = \boxed{\frac{\rho}{1 - (1 - L \times \epsilon_D)\rho}}$$

- Nests Perfect Competition $\theta = 0$, Monopoly $\theta = 1$, Cournot $\theta = \frac{1}{N}$

Extension Here: Incidence of Input Taxes

Incidence of input taxes differ from incidence of output taxes

- Key difference: Firms can substitute away from a shock to input prices; only pay input tax on each unit purchased

Definition: Cost shift rate

$$\gamma \equiv \frac{dmc}{dt}$$

Incidence of Input Tax under Imperfect Competition

$$I_{Input}^{Oligopoly} = \frac{\rho}{\gamma - (1 - L \times \epsilon_D)\rho}$$

General formula for input tax based on 4 key parameters:

- Pass-through (ρ); markup (L); demand elasticity (ϵ_D); cost-shift rate (γ)
- These parameters characterize incidence of changes in input prices for a wide variety of demand systems and markets structures

Empirical Approach

Bounding Approach: Estimate cost-pass through only to bound incidence between the perfect competition and monopoly cases

General Approach: Draw upon methods to jointly estimate markups and MC using production and price data (Hall 1988; De Loecker, Warzynski 2012)

- Use plant-level data to estimate production functions
- Use optimal input choices and production to infer productivity and markups
- Marginal costs are backed out in standard IO way: Price$=$MC$\times$Markup
- Examine how marginal costs, markups, and unit prices are affected by (plausibly exogenous) changes in energy costs

Data

Census of Manufacturers, 1972-1997

- Quinquennial plant-product-year level micro data from U.S. Census.
- Sample restrictions:
  - Industries that report quantities of homogenous products (unit prices)
  - Single product plants (50%+ specialization)
  - Drop imputed prices/quantities (unisys recovered imputes)
- Boxes, Bread, Cement, Concrete, Gas, Plywood

Manufacturing Energy Consumption Survey

- Plant-level survey on energy inputs (i.e. coal, gas, oil, electricity)
- Construct fuel input shares by industry$\times$region$\times$year

Energy Information Administration's State Energy Data System (SEDS)

- Electricity generation fossil fuel input shares (BTU) at State$\times$Year level
- National fuel prices (i.e. coal, natural gas, petroleum)

Recovering Markups: Summary

1. Firm's FOC implies:
   - Markup equals output elasticity divided by revenue share
   - For a flexible input like materials

$$\underbrace{\frac{P_{it}}{\lambda_{it}}}_{Markup} = \underbrace{\left[\frac{\partial Q_{it}(\cdot)}{\partial V_{it}} \frac{V_{it}}{Q_{it}}\right]}_{Output \ \ Elasticity} \underbrace{\left[\frac{P^V_{it} V_{it}}{P_{it} Q_{it}}\right]^{-1}}_{Revenue \ \ Share}$$

   - Intuition: Under imperfect competition, input growth is associated with disproportional revenue growth

2. Estimate output elasticity via production functions (Ackerberg et al. 2015)
   - Translog, gross-output production function with 3 factors (K, L, M)
   - Output is quantity (not revenue), avoiding output price bias

3. Compute marginal costs from price = marginal cost × markup

Production Function Estimation and Output Elasticities

	Energy Cost Share (1)	Output Elasticities: Labor (2)	Materials (3)	Capital (4)	Returns to Scale (5)	Markup (6)	Observations (7)
Boxes	0.02	0.04	0.95	0.04	1.00	1.47	1414
Bread	0.02	0.28	0.63	0.09	1.13	1.20	248
Cement	0.33	0.91	1.08	0.19	2.46	2.30	229
Concrete	0.02	0.11	0.68	0.16	1.09	1.12	3369
Gasoline	0.88	0.01	0.99	0.03	1.02	1.11	284
Plywood	0.02	0.02	0.95	0.11	0.92	1.48	139
Mean	0.02	0.10	0.070	0.14	1.09	1.15	5683

Note: Translog, 3-factor (K, L, M), gross-output production function. Materials include electricity+fuels. This table shows mean values of energy cost shares, output elasticities, and markups. An observation is a plant-year.

How do Plant Level Marginal Costs, Markups, and Prices respond to ΔEnergy price?

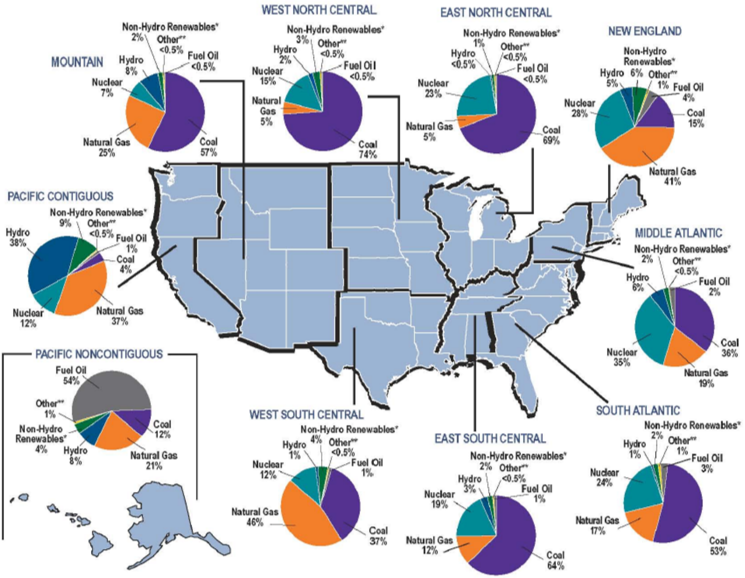
Energy prices are likely endogenous:

- e.g., correlated with local demand

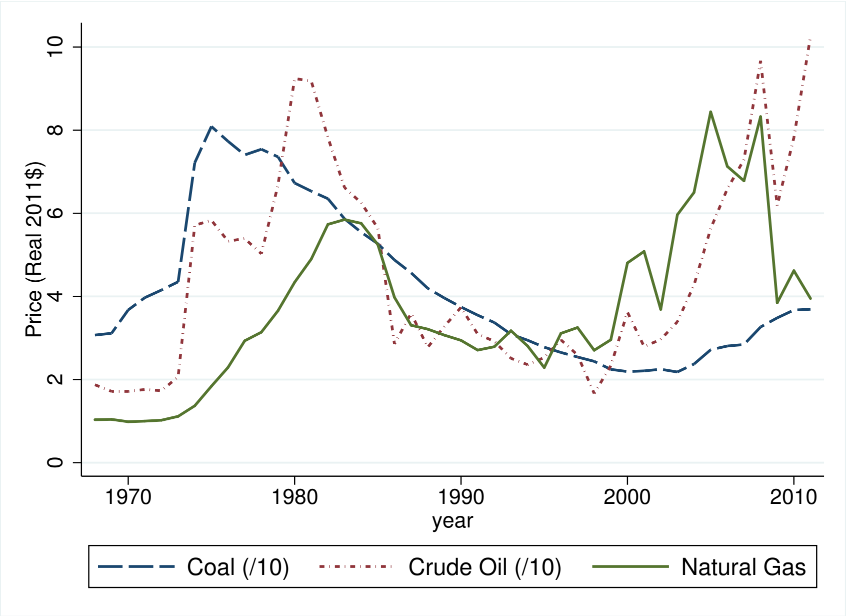
Two Research Designs:

1. Exploit balkanized nature of U.S. electricity markets
   - Different regions use different fuel mixes to generate electricity
2. Differential fuel input usage by industry
   - Industries use different fuel/energy inputs for production

Different Regions Use Different Fuel Mixes to Generate Electricity



National Variation in Fuel Prices Over Time



How do Plant Level Marginal Costs, Markups, and Prices respond to ΔEnergy price?

Research Design #1: Regions use different fuels to generate electricity

$$Y_{it} = \sum_{f \in \{\text{coal, gas, oil}\}} \left[\underbrace{\beta^f [E^f_{t,-s} \times Share^f_{st-2}]}_{\text{variables of interest}} \right] + X'_{it}\gamma + \eta_i + \epsilon_{it}$$

- Y_{it}: Plant-level Marginal Costs, Markups, and Prices
- $E^f_{t,-s}$ National (leave out mean) fuel prices
- σ^f_{st-k} State generation shares, lagged k years

Other Controls:

- X_{it}: vector of controls
  - e.g. ind-year FE, region year FE, state-trends, $E^f_{t,-s}$, $Share^f_{st-2}$
- η_i: plant fixed effects

Research Design #2

Increases in Electricity Fuel Prices Increase Marginal Costs

Research Design #1

	Lag (t-0) (1)	Lag (t-2) (2)	Lag (t-5) (3)	Lag (t-0) (4)	Lag (t-2) (5)	Lag (t-5) (6)
Coal Price $\times$ Coal Share	0.092	0.156	-0.110	0.357	0.374	0.123
	(0.387)	(0.363)	(0.311)	(0.244)	(0.293)	(0.255)
Gas Price $\times$ Gas Share	0.779***	0.788***	0.866***	0.235***	0.225***	0.291***
	(0.175)	(0.140)	(0.191)	(0.086)	(0.084)	(0.061)
Oil Price $\times$ Oil Share	0.136	0.229	0.013	-0.070	0.047	-0.029
	(0.341)	(0.290)	(0.207)	(0.121)	(0.118)	(0.139)
Plant FE	X	X	X	X	X	X
Year FE	X	X	X			
State Trends	X	X	X	X	X	X
Region-Year FE				X	X	X
Product-Year FE				X	X	X

Notes: 6 regressions, 1 per column. Observation = plant-year. Energy data from EIA-SEDS, state-level.

Marginal costs estimated using 3 factor (K, L, M), translog production function. S.E. clustered by state.

Interpretation [Column 4-6, Gas]: 1% increase in gas price $\Rightarrow$ 0.291% increase in marginal costs for state with 100% gas generation share.

- Average gas generation share is 25% $\Rightarrow$ 0.07% increase in marginal costs

Increases in Electricity Fuel Prices Increase Output Prices [Less]

Research Design #1

	Lag (t-0) (1)	Lag (t-2) (2)	Lag (t-5) (3)	Lag (t-0) (4)	Lag (t-2) (5)	Lag (t-5) (6)
Coal Price × Coal Share	0.081	0.063	-0.061	0.259	0.159	0.065
	(0.259)	(0.254)	(0.197)	(0.263)	(0.257)	(0.223)
Gas Price × Gas Share	0.491***	0.502***	0.532***	0.186**	0.204***	0.222***
	(0.109)	(0.088)	(0.101)	(0.074)	(0.061)	(0.054)
Oil Price × Oil Share	0.101	0.172	0.078	-0.008	0.057	0.079
	(0.181)	(0.168)	(0.131)	(0.102)	(0.094)	(0.108)
Plant FE	X	X	X	X	X	X
Year FE	X	X	X			
State Trends	X	X	X	X	X	X
Region-Year FE				X	X	X
Product-Year FE				X	X	X

Notes: 6 regressions, 1 per column. Observation = plant-year. Energy data from EIA-SEDS, state-level. Standard errors clustered by state.

Interpretation [Column 4-6, Gas]: 1% increase in gas price ⇒ $0.222 \times 0.25 = 0.07$ percent increase in unit prices

Increases in Electricity Fuel Prices Decrease Markups

Research Design #1

	Lag (t-0) (1)	Lag (t-2) (2)	Lag (t-5) (3)	Lag (t-0) (4)	Lag (t-2) (5)	Lag (t-5) (6)
Coal Price × Coal Share	-0.012	-0.092	0.049	-0.098	-0.215	-0.058
	(0.220)	(0.183)	(0.171)	(0.156)	(0.172)	(0.172)
Gas Price × Gas Share	-0.288***	-0.286***	-0.334***	-0.049	-0.021	-0.069*
	(0.080)	(0.066)	(0.096)	(0.045)	(0.053)	(0.038)
Oil Price × Oil Share	-0.035	-0.056	0.065	0.062	0.010	0.107
	(0.181)	(0.134)	(0.097)	(0.090)	(0.069)	(0.077)
Plant FE	X	X	X	X	X	X
Year FE	X	X	X			
State Trends	X	X	X	X	X	X
Region-Year FE				X	X	X
Product-Year FE				X	X	X

Notes: 6 regressions, 1 per column. Observation = plant-year. Energy data from EIA-SEDS, state-level. Markups estimated using 3 factor (K, L, M), translog production function. Standard errors clustered by state.

Interpretation [Columns 4-6, Gas]: 1% increase in gas price ⇒ $-0.069 \times 0.25 = -0.02$ percent decrease in markups

▸ Research Design #2

To What Extent are Plant-level Changes in MC Passed Through to Price?

Standard Pass-Through Regression: Price against Marginal Cost

$$p_{it} = \rho_{MC,\epsilon} mc_{it} + X'_{it}\gamma + \eta_i + \epsilon_{it}$$

Instrument mc_{it} **with** $[E_{t,-s} \times Share_{st-k}]$ (i.e. fuel share $\times$ fuel price)

- Policy Relevant LATE: What is the effect of energy-price driven change in marginal costs on output prices?
- Note: $\rho_{MC,\epsilon}$ = regression coefficient; marginal cost pass-through elasticity

Marginal Cost Pass-Through: Electricity Shift-Share IV

	(1) Lag (t-0)	(2) Lag (t-2)	(3) Lag (t-5)	(4) Lag (t-0)	(5) Lag (t-2)	(6) Lag (t-5)
	Panel A: Electricity Shift-Share Instrument					
Marginal Costs	0.628***	0.623***	0.625***	0.660***	0.654***	0.715***
	(0.031)	(0.031)	(0.029)	(0.099)	(0.088)	(0.086)
N	5892	5892	5892	5892	5892	5892
First Stage F-Statistic	9.53	14.33	6.99	8.89	3.95	12.09
Pass-Through Rate	0.72	0.72	0.72	0.76	0.75	0.82
Plant FE	X	X	X	X	X	X
Year FE	X	X	X			
State Trends	X	X	X	X	X	X
Product-Year FE				X	X	X
Region-Year FE				X	X	X

Notes: 6 regressions, 1 per column. Observation = plant-year. Energy data from EIA-SEDS, state-level. Markups estimated using 3 factor (K, L, M), translog production function. Standard errors clustered by state.

▸ OLS

▸ Research Design #2

Pass-Through Elasticity by Industry - Instrumental Variables

	(1) Boxes	(2) Bread	(3) Cement	(4) Concrete	(5) Gasoline	(6) Plywood
Marginal Costs	0.963***	0.681***	0.775***	0.711***	0.327**	0.692***
	(0.038)	(0.150)	(0.087)	(0.082)	(0.143)	(0.082)
N	1414	308	293	3369	345	163
Pass-Through Rate	1.42	0.82	1.78	0.80	0.36	1.02
First Stage F-Statistic	23.41	1.67	49.29	23.36	2.43	38.55
Plant FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Trends FE	X	X	X	X	X	X

Notes: 6 regressions; one per column. Each column represents a separate sample, where the sample is indicated in the column headings. Observation = plant-year. Dependent variable = plant-level output-price.

Demand Forms

Incidence of Input Taxes under Imperfect Competition

Incidence of Input Tax under Imperfect Competition

$$
\begin{aligned}
I_{Input}^{Oligopoly} &= \frac{\rho}{\gamma - (1 - L \times \epsilon_D)\rho} \\
&= \frac{\rho_{MC}}{1 - (1 - L \times \epsilon_D)\rho_{MC}}
\end{aligned}
$$

General formula for input tax now based on 3 key parameters:

- Marginal cost pass-through, ρ_{MC} [Estimated above]
- Lerner Index (Markup), L [Estimated above]
- Demand elasticity, ϵ_D [Using Foster, Syverson, Haltiwanger (2008) methods]

Welfare Incidence: Symmetric and Asymmetric Oligopoly

Rewrite Incidence, $I \equiv \frac{dCS/dt}{dCS/dt + dPS/dt}$

- How much do consumers bear as % of loss [gain?] to producers+consumers?

	(1) Boxes	(2) Bread	(3) Cement	(4) Concrete	(5) Gasoline	(6) Plywood
	Panel A: Incidence Components					
MC Pass-Through (ρ_{MC})	1.43	0.69	1.81	0.74	0.31	1.08
Demand Elasticity (ϵ_D)	3.24	2.42	1.82	5.53	8.70	1.39
Mean Lerner Index (L)	0.33	0.18	0.57	0.13	0.12	0.41
	Panel B: Consumer Share of Burden (by Market Structure)					
Symmetric Oligopoly	0.57	0.53	0.63	0.49	0.24	0.67
Asymmetric Oligopoly	0.60	0.66	0.69	0.63	0.25	0.87
Monopoly	0.59	0.41	0.64	0.43	0.24	0.52
Perfect Competition	1.43	0.69	1.81	0.74	0.31	1.08

Demand elasticity, ϵ_D [Using Foster, Syverson, Haltiwanger (2008)]. Estimating Demand

Bounding Exercise

How to relax assumptions pertaining to production function estimation?

- Use incidence from perfect comp. and monopoly to bound more general case

$$I^{Competitive} = \frac{\rho}{\gamma - \rho} \qquad\qquad I^{Monopoly} = \frac{\rho}{\gamma}$$

- Only requires knowing pass-through rate and cost-shift rate
  - Pass-through rate we can directly estimate
  - Cost shift rate can be parameterized without having to estimate markups, marginal costs, and/or production functions

Welfare Incidence: Perfect Competition and Monopoly

Rewrite Incidence, $I \equiv \frac{dCS/dt}{dCS/dt + dPS/dt}$

- How much do consumers bear as % of loss [gain?] to producers+consumers?

	(1) Boxes	(2) Bread	(3) Cement	(4) Concrete	(5) Gasoline	(6) Plywood
	Panel A: Incidence Components					
MC Pass-Through (ρ_{MC})	1.43	0.69	1.81	0.74	0.31	1.08
Demand Elasticity (ϵ_D)	3.24	2.42	1.82	5.53	8.70	1.39
Mean Lerner Index (L)	0.33	0.18	0.57	0.13	0.12	0.41
	Panel B: Consumer Share of Burden (by Market Structure)					
Symmetric Oligopoly	0.57	0.53	0.63	0.49	0.24	0.67
Asymmetric Oligopoly	0.60	0.66	0.69	0.63	0.25	0.87
Monopoly	0.59	0.41	0.64	0.43	0.24	0.52
Perfect Competition	1.43	0.69	1.81	0.74	0.31	1.08

Demand elasticity, ϵ_D [Using Foster, Syverson, Haltiwanger (2008)].

Wrapping Up

This paper: methodology to estimate incidence of cost shocks under relatively weak assumptions on preferences or competition

- Prices (and extent to which they respond to cost shocks) are sufficient statistics for primitive demand and supply parameters.
- Additional info on markups + demand elasticities $\Rightarrow$ characterize incidence under arbitrary forms of imperfect competition

Findings: Standard methods overstate share of burden for consumers.

- Reasons: incomplete pass-through, perfect competition

Muehlegger and Sweeney (2017)

What is the question, and why is it interesting?

- Fracking reduced costs for US oil producers. How do these costs reductions affect equilibrium outcomes?
- Pass through may tell us about nature of competition + incidence

Why is the existing literature crappy, nonexistent, and/or unresolved

- Disparate findings in pass-through lit (e.g. average pass-through rates ignoring nature of competition and/or type of cost shock)

What are the authors going to do to solve it?

- Take seriously determinants of pass-through heterogeneity within an industry (oil refining)
- Show how and why earlier findings on pass-through differ (e.g. market-level vs. plant-level input cost shocks)
- Use administrative refinery production data (observe prices + costs)

Muehlegger and Sweeney (2017)

Motivation: Pass-Through and Imperfect Competition

- Simple oligopoly models $\Rightarrow$ Δfirm's costs affect prices through own decisions, but also indirectly through strategic response by competitors.
- Magnitude of strategic response depends on nature of competition
- Also, type of shock matters (firm versus market)

Muehlegger and Sweeney (2017)

Existing Empirical Challenges

1. Data: need detailed data on both prices and costs for all firms in a market (often unobserved)
2. Competition: often difficult to observe which pairs of firms are close competitors
3. Causality: needs variation in input shocks both within markets and across different market structures.

Solutions: Admin data on output prices and input costs + shipment destinations (e.g. competitors) + institutional details which give rise to input cost variation

Theory: Pass-through and imperfect competition

Define $c_i = \overline{\alpha} + \alpha_i$ as MC faced by firm i (i.e. sum of a shared (market-wide) cost ($\overline{\alpha}$) and firm-specific cost (α_i).

Let $\boldsymbol{\rho}_{\boldsymbol{\alpha}}$ denote the pass-through of a shock α onto the vector of firm-specific prices.

$$\boldsymbol{\rho}_{\boldsymbol{\alpha}} = \sum_i \frac{\partial \boldsymbol{p}}{\partial \sigma_i}\left(\frac{\partial \sigma_i}{\partial \alpha_i} + \sum_{j \neq i} \frac{\partial \sigma_i}{\partial \sigma_j}\frac{d\sigma_j}{d\alpha}\right)$$

where σ is a single dimensional strategic variable chosen by firms to maximize profits (i.e. will differ based on market structure)

Implications: Cost shock affects firm's choice of strategy σ directly through firm's own costs and indirectly, in response to strategic choice of competitors.

- Different market structures have different strategic choices $\Rightarrow$ different pass-through implications

Cournot Competition

Contrast pass-through of firm-specific shock, $\boldsymbol{\rho_{\alpha_i}}$ with pass-through of market-wide shock, $\boldsymbol{\rho_{\bar{\alpha}}}$

Cournot: Strategic variable σ_i is quantity produced by a firm.

- How does strategy and hence equilibrium prices change WRT to α_i or $\bar{\alpha}$

$$\frac{dQ}{d\alpha_i} = \frac{1}{(n+1)P'(Q) + QP''(Q)}; \quad \frac{dQ}{d\bar{\alpha}} = \frac{n}{(n+1)P'(Q) + QP''(Q)}.$$

Implications: Consider equally sized cost shock: one that affects a single firm and another to all firms...

1. Firm specific shock: As n increases, change in affected firm's production is offset by increase at other firms (reducing pass-through rate)
2. Common shock: causes all firms to lower production, and pass-through to increase with n
3. Note: firm-specific shock has similar effect on market price (regardless of firm's initial market share or MC)

Differentiated Nash-in-Prices

Differentiation could reflect the geographic nature of delivery and competition.

- Strategic variable σ_i represents the price set by a firm

Pass-through depends on: (1) direct effect on firm i's strategy, (2) indirect response to a competitor shock, and (3) degree of strategic complementarity.

Consider ratio of pass-through for firm vs. common shock (2 firm case):

$$\frac{\boldsymbol{\rho_{\alpha_i}}}{\boldsymbol{\rho_{\bar{\alpha}}}} = \frac{\frac{\partial \sigma_i}{\partial \alpha_i}}{\frac{\partial \sigma_i}{\partial \alpha_i} + \frac{\partial \sigma_i}{\partial \sigma_j}\frac{\partial \sigma_j}{\partial \alpha_j}}.$$

Implications: Relative to Cournot

- As products become closer substitutes (reflected as an increase in $\partial\sigma_i/\partial\sigma_j$), competitor's cost shock exerts an increasingly large impact on the firm i's optimal price and pass-through rates of two different shocks diverge.
- In Cournot, pass-through was independent of identity of affected party.

Pass-through under different forms of competition

Takeaways:

- Pass-through depends on nature of cost shock.
- Firm-specific shocks $\Rightarrow$ lower pass-through rates than common shocks.
- Patterns of pass-through distinguish the nature of competition.
- Under Cournot, cost shocks have identical effects, regardless of affected party
- Differentiated products: degree of competition between two parties plays central role in determining pass-through of own and competitor cost shocks.

Muehlegger and Sweeney (2017): Data

Universe of oil refiners in the United States from Energy Information Admin (EIA)

- Regional crude procurement costs at firm-month level
- Detailed production decisions for each refinery that firm owns
- Prices and quantities for each product at firm-state-month

Comparative Advantage of Data: Overcome two challenges in literature:

1. Directly observe firm-level prices and costs (as opposed to estimate costs)
2. Can distinguish between shocks affecting close rivals and/or cost shocks affecting firms that do not directly compete

Some Challenges:

1. crude costs are only reported at the firm-PADD level
2. sales are reported at the firm level, not the refinery level (i.e. not sure which refinery's input costs should be associated with a sale in given region)

Petroleum Refining

Some institutional details: useful for empirical setup

- Oil markets thought to be well integrated, hence input cost variation should be pretty small
- For a variety of reasons, shale boom temporarily reduced input costs for refineries near deposits
- Refineries must adjust technology for different types of crude inputs, which takes time

End Result: Observed reductions in input costs for some refiners, while the costs for other firms (sometimes in similar areas + identical products) = unchanged.

Empirical Setup

Standard pass-through regression may be misspecified in imperfectly competitive settings

$$Price_{fmt} = \alpha Cost_{ft} + X'_{fmt}\delta + \epsilon_{fmt}$$

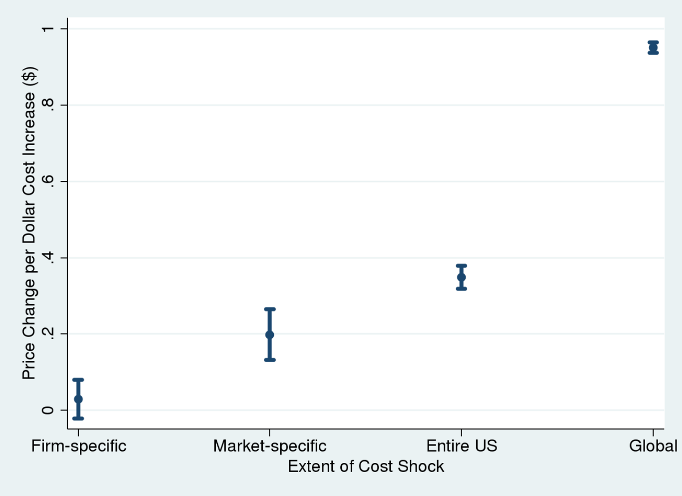
1. OVB: e.g. realized prices will be a function of both own costs and competitors' costs
   - Solution: add in observables on rival's cost
2. Measurement error: how to weight rivals costs?
3. Controls affect nature of cost shock (e.g. fixed effects shut down market level variation but are important for controlling bias)

Table 4: Pass-Through Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own	0.0343***	0.0441***	0.0433***	0.0497***	0.0420***	-0.00599	0.00576
	(0.0115)	(0.0121)	(0.0120)	(0.0127)	(0.0122)	(0.0266)	(0.0269)
Padd Avg	0.0632***						
	(0.0186)						
Rival		0.0788***	0.0758***	0.131***	0.0612***	0.0928**	0.0687*
		(0.0182)	(0.0180)	(0.0197)	(0.0159)	(0.0416)	(0.0352)
NonRival			0.168***	0.811***	0.245***	0.000348	0.173***
			(0.0428)	(0.0231)	(0.0198)	(0.106)	(0.0334)
Brent Spot					0.611***		0.700***
					(0.00971)		(0.00946)
Time FEs	Y-M	Y-M	Y-M	Y,M	Y,M	Y-M	Y,M
IV						Yes	Yes
first F						900	963
N	55568	55568	55568	55568	55568	55568	55568
r2	0.975	0.975	0.975	0.951	0.956	0.975	0.956

This table presents the results of estimating Equation (7) using total average wholesale prices as the dependent variable. Panel (a) is estimated at the firm-state-month level, and includes firm-state fixed effects; Panel (b) is estimated at the firm level and includes firm fixed effects. Time FEs "Y-M" reflect year-month dummies, while "Y,M" implies year and month dummies. Rival costs include the average crude price of other firms selling into the same market each month, and non-rival costs are the average cost of all other firms, weighted by the inverse shipping cost of supplying the market. Standard errors are presented in parentheses, clustered at the firm-state level in panel (a) and the firm level in panel (b). All models include demand shifters (state population, income, heating and cooling degree days) and supply shifters (diesel and gasoline shares, proportion of retail sales, API gravity, and operating refinery capacity).

Implied Pass-Through by Shock Type



Estimates from model (5) of panel (b) in Table 4.

Wrap-up: Muehlegger and Sweeney (2017)

Findings

- Controls matter: with time$\times$geography dummies, little pass-through
- Relaxing controls: 20% of market specific costs, 35% of national cost shocks, and 95% of global cost shocks are passed through

Contribution

- One of the first empirical papers to think formally about strategic interactions in the context of pass-through heterogeneity
- Reconciling disparate findings in the literature

Other papers using pass-through to parameterize welfare / incidence / market structure

Long pass-through literature in public finance and macro/international finance

- More recent developments to think about pass-through and market power (stemming from Weyl and Fabinger 2013)

Some recent papers in trade/development

- Atkin and Donaldson (2015): How large are intra-national trade costs and what fraction of that is due to market power in intermediaries?
- Falcao-Berquist (2017), Casaburi and Reed (2017): What does pass-through tell us about market structure in trade intermediaries?

Energy and Environment

- Fabra and Reguant (2014): Pass-through of emissions costs
- Miller (2016): Cement energy cost pass-through
- Stolper (2016): Retail gas pass-through
- Preonas (2018): Coal/CO_2 pass-through