Unraveling Firms: Demand, Productivity and Markups Heterogeneity

Emanuele Forlani (University of Pavia and LdA)
Ralf Martin (Imperial College London, CEP, and Grantham)
Giordano Mion (University of Surrey, CEP, and CEPR)
Mirabelle Muûls (Imperial College London, CEP, and Grantham)

ECB, Frankfurt, 26-06-2015

Motivation

There is a large and influential body of research concerned with firm TFP estimations.

Motivation

There is a large and influential body of research concerned with firm TFP estimations.

- Econometric Models: Based on Olley and Pakes (1996) seminal contribution with a proxy variable approach to tackle the issue of omitted (to the econometrician) variables.

Motivation

There is a large and influential body of research concerned with firm TFP estimations.

- Econometric Models: Based on Olley and Pakes (1996) seminal contribution with a proxy variable approach to tackle the issue of omitted (to the econometrician) variables.

- Applied contributions: Wide ranging use of estimated firm TFP as a key variable: business cycles (Macro literature), firm size distribution, survival and growth (IO literature), self selection of firms into export status and intensive margin (Trade literature), etc.

Motivation

Yet there is a a growing interest in other dimensions of firm heterogeneity and in particular demand. ▸ importance of demand

Motivation

Yet there is a a growing interest in other dimensions of firm heterogeneity and in particular demand. ▸ importance of demand

By means of our framework we are able to unravel standard measures of revenue productivity (productivity measured with either value added or revenue as opposed to physical quantity) into 3 components: **physical productivity, consumers' appreciation for a firm's products and markups**.

Motivation

Yet there is a a growing interest in other dimensions of firm heterogeneity and in particular demand. ▸ importance of demand

By means of our framework we are able to unravel standard measures of revenue productivity (productivity measured with either value added or revenue as opposed to physical quantity) into 3 components: **physical productivity, consumers' appreciation for a firm's products and markups**.

This allow us to have a fresh look at a number of stylized facts based on revenue productivity and gain sharper and deeper insights.

Our Contribution

- Provide a framework simultaneously allowing for heterogeneity in demand, productivity and markups across firms while leaving the correlation among the three unrestricted (unlike in Foster et al., 2008)

Our Contribution

- Provide a framework simultaneously allowing for heterogeneity in demand, productivity and markups across firms while leaving the correlation among the three unrestricted (unlike in Foster et al., 2008)

    1. We are able to do this by imposing a more explicit structure (on preferences and firm behavior).

Our Contribution

- Provide a framework simultaneously allowing for heterogeneity in demand, productivity and markups across firms while leaving the correlation among the three unrestricted (unlike in Foster et al., 2008)

  1. We are able to do this by imposing a more explicit structure (on preferences and firm behavior).
  2. We do not rely on the proxy variable approach and so do not need proxies for markups.

Our Contribution

- Provide a framework simultaneously allowing for heterogeneity in demand, productivity and markups across firms while leaving the correlation among the three unrestricted (unlike in Foster et al., 2008)

  1. We are able to do this by imposing a more explicit structure (on preferences and firm behavior).
  2. We do not rely on the proxy variable approach and so do not need proxies for markups.

- We use production data on Belgian firms to quantify productivity, markups and demand heterogeneity and

Our Contribution

- Provide a framework simultaneously allowing for heterogeneity in demand, productivity and markups across firms while leaving the correlation among the three unrestricted (unlike in Foster et al., 2008)

  1. We are able to do this by imposing a more explicit structure (on preferences and firm behavior).
  2. We do not rely on the proxy variable approach and so do not need proxies for markups.

- We use production data on Belgian firms to quantify productivity, markups and demand heterogeneity and

  1. Show how they are correlated among them as well as with revenue TFP measures.

Our Contribution

- Provide a framework simultaneously allowing for heterogeneity in demand, productivity and markups across firms while leaving the correlation among the three unrestricted (unlike in Foster et al., 2008)

  1. We are able to do this by imposing a more explicit structure (on preferences and firm behavior).
  2. We do not rely on the proxy variable approach and so do not need proxies for markups.

- We use production data on Belgian firms to quantify productivity, markups and demand heterogeneity and

  1. Show how they are correlated among them as well as with revenue TFP measures.
  2. Show how and to what extent they allow to say something about two key outcomes: firm size and export status.

Road Map

A short summary of the baseline econometric model (we can allow for several extensions)

Road Map

A short summary of the baseline econometric model (we can allow for several extensions)

Data

Road Map

A short summary of the baseline econometric model (we can allow for several extensions)

Data

Estimations

Road Map

A short summary of the baseline econometric model (we can allow for several extensions)

Data

Estimations

Descriptives and correlation analysis

Road Map

A short summary of the baseline econometric model (we can allow for several extensions)

Data

Estimations

Descriptives and correlation analysis

Relationship with revenue TFP

Road Map

A short summary of the baseline econometric model (we can allow for several extensions)

Data

Estimations

Descriptives and correlation analysis

Relationship with revenue TFP

Links with firm size and export status

The Model

We share most of the structure and assumptions made in De Loecker and Warzynski (2012). With respect to them we further:

- Assume that firms maximize profits and that the market structure in which they operate is monopolistic competition

The Model

We share most of the structure and assumptions made in De Loecker and Warzynski (2012). With respect to them we further:

- Assume that firms maximize profits and that the market structure in which they operate is monopolistic competition
- Introduce demand shocks while imposing some restrictions on the way the enter Utility

The Model

We share most of the structure and assumptions made in De Loecker and Warzynski (2012). With respect to them we further:

- Assume that firms maximize profits and that the market structure in which they operate is monopolistic competition
- Introduce demand shocks while imposing some restrictions on the way the enter Utility

At the same time we depart from the proxy variable approach and use the structure imposed by our assumptions to back-out relevant parameters via manipulating equations.

The Model: Cost Minimization; Flexible and fixed factors

We have 3 production factors: labour (L), intermediate inputs (M) and capital (K). Whereas labour and materials are perfectly flexible, capital is fixed in the short run. Consequently, firms are dealing with the following short run cost minimization problem

The Model: Cost Minimization; Flexible and fixed factors

We have 3 production factors: labour (L), intermediate inputs (M) and capital (K). Whereas labour and materials are perfectly flexible, capital is fixed in the short run. Consequently, firms are dealing with the following short run cost minimization problem

$$\min_{L,M} \{L_{it} W_L + M_{it} W_M\} \text{ s.t. } Q_{it} = A_{it} L_{it}^{\alpha_L} M_{it}^{\alpha_M} K_{it}^{\gamma - \alpha_M - \alpha_L}$$

where A_{it} is firm TFP.

The Model: Cost Minimization; Flexible and fixed factors

We have 3 production factors: labour (L), intermediate inputs (M) and capital (K). Whereas labour and materials are perfectly flexible, capital is fixed in the short run. Consequently, firms are dealing with the following short run cost minimization problem

$$\min_{L,M} \{L_{it} W_L + M_{it} W_M\} \text{ s.t. } Q_{it} = A_{it} L_{it}^{\alpha_L} M_{it}^{\alpha_M} K_{it}^{\gamma - \alpha_M - \alpha_L}$$

where A_{it} is firm TFP.

If we were to regress log quantity on log capital, log labour and log materials to get log A_{it} as a residual we would make a mistake. Indeed A_{it} is endogenous because it is known to the firm but not to the econometrician.

The Model: Cost Minimization; Flexible and fixed factors

We have 3 production factors: labour (L), intermediate inputs (M) and capital (K). Whereas labour and materials are perfectly flexible, capital is fixed in the short run. Consequently, firms are dealing with the following short run cost minimization problem

$$\min_{L,M} \{L_{it} W_L + M_{it} W_M\} \text{ s.t. } Q_{it} = A_{it} L_{it}^{\alpha_L} M_{it}^{\alpha_M} K_{it}^{\gamma - \alpha_M - \alpha_L}$$

where A_{it} is firm TFP.

If we were to regress log quantity on log capital, log labour and log materials to get log A_{it} as a residual we would make a mistake. Indeed A_{it} is endogenous because it is known to the firm but not to the econometrician.

We use here Cobb-Douglas but we could as well use Translog.

The Model: Preferences

We impose some conditions on preferences (1st departure from DLW).

The Model: Preferences

We impose some conditions on preferences (1st departure from DLW).

In the end we want that the elasticity of prices with respect to output quantity differs from the elasticity of prices w.r.t to the demand shock by one.

The Model: Preferences

We impose some conditions on preferences (1st departure from DLW).

In the end we want that the elasticity of prices with respect to output quantity differs from the elasticity of prices w.r.t to the demand shock by one.

There are various ways of achieving this:

1. Start from direct utility
2. Start from demand and work out some constraints

The Model: Preferences

We impose some conditions on preferences (1st departure from DLW).

In the end we want that the elasticity of prices with respect to output quantity differs from the elasticity of prices w.r.t to the demand shock by one.

There are various ways of achieving this:

1. Start from direct utility
2. Start from demand and work out some constraints

Today I will present results based on the Generalized CES: Spence (1976)

$$U(\tilde{Q}_t) = \int_{i \in I_t} a_{it} \left(\tilde{Q}_{it} \right)^{b_{it}} \mathrm{d}i = \int_{i \in I_t} a_{it} \Lambda_{it}^{b_{it}} \left(Q_{it} \right)^{b_{it}} \mathrm{d}i$$

▸ Preferences

The Model: Markups, Demand and Productivity shocks

- We assume, as standard, that productivity follows a Markov process. We make the same assumption for demand shocks. In the case of a linear (we can generalize to non-linear as well introduce correlated unobserved heterogeneity) Markov process this means:

$$a_{it} = \phi_a a_{it-1} + \nu_{ait}$$
$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}$$

The Model: Markups, Demand and Productivity shocks

- We assume, as standard, that productivity follows a Markov process. We make the same assumption for demand shocks. In the case of a linear (we can generalize to non-linear as well introduce correlated unobserved heterogeneity) Markov process this means:

$$a_{it} = \phi_a a_{it-1} + \nu_{ait}$$
$$\lambda_{it} = \phi_\lambda \lambda_{it-1} + \nu_{\lambda it}$$

- As for markups we do not need to make specific assumptions about the process they follow. For each firm i and time t our model implies (Hall, 1986; DLW, 2012):

$$\mu_{it} = \frac{\alpha_M}{s_{Mit}}$$

where α_M is the production function coefficient corresponding to the variable input materials and s_{Mit} is the share of expenditure on materials in revenue (we could as well use another variable input).

The Model: Estimation

We do not need to use a proxy variable approach. (3rd departure from DLW)

The Model: Estimation

We do not need to use a proxy variable approach. (3rd departure from DLW) Given our assumptions we can simply manipulate the equations of the model. In the case of the Generalized CES the revenue equation can be rewritten as:

$$
\begin{aligned}
LHS_{it} &= \frac{\gamma}{\alpha_M} k_{it} + \phi_a LHS_{it-1} - \phi_a \frac{\gamma}{\alpha_M} k_{it-1} \\
&+ (\phi_\lambda - \phi_a) \left(\frac{r_{it-1}}{s_{Mit-1}} - \frac{1}{\alpha_M} q_{it-1} \right) + \frac{1}{\alpha_M} (\nu_{ait} + \nu_{\lambda it}) \quad (1)
\end{aligned}
$$

where $LHS_{it} = \frac{r_i - s_{Li}(l_i - k_i) - s_{Mi}(m_i - k_i)}{s_{Mi}}$ is a function of observables.

The Model: Estimation

We can rewrite (1) as:

$$LHS_{it} = b_1 z_{1it} + b_2 z_{2it} + b_3 z_{3it} + b_4 z_{4it} + b_5 z_{5it} + u_{it}$$

where $z_{1it} = k_{it}$, $z_{2it} = LHS_{it-1}$, $z_{3it} = k_{it-1}$, $z_{4it} = \frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it} = q_{it-1}$, $u_{it} = \frac{1}{\alpha_M}(\nu_{ait} + \nu_{\lambda it})$ as well as $b_1 = \frac{\gamma}{\alpha_M}$, $b_2 = \phi_a$, $b_3 = -\phi_a \frac{\gamma}{\alpha_M}$, $b_4 = (\phi_\lambda - \phi_a)$ and $b_5 = -(\phi_\lambda - \phi_a)\frac{1}{\alpha_M}$.

The Model: Estimation

We can rewrite (1) as:

$$LHS_{it} = b_1 z_{1it} + b_2 z_{2it} + b_3 z_{3it} + b_4 z_{4it} + b_5 z_{5it} + u_{it}$$

where $z_{1it}=k_{it}$, $z_{2it}=LHS_{it-1}$, $z_{3it}=k_{it-1}$, $z_{4it}=\frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it}=q_{it-1}$,
$u_{it}=\frac{1}{\alpha_M}\left(\nu_{ait}+\nu_{\lambda it}\right)$ as well as $b_1=\frac{\gamma}{\alpha_M}$, $b_2=\phi_a$, $b_3=-\phi_a\frac{\gamma}{\alpha_M}$, $b_4=(\phi_\lambda-\phi_a)$
and $b_5=-\left(\phi_\lambda-\phi_a\right)\frac{1}{\alpha_M}$.

Given our assumptions the error term u_{it} is uncorrelated with all of the regressors. Therefore this equations can be estimated via simple OLS to get estimates for two key parameters: $\frac{\gamma}{\alpha_M}$ and ϕ_a.

The Model: Estimation

We then use these estimates in a 2nd stage equation. In the case of the Generalized CES the quantity equation can be manipulated to get ($\beta = \frac{\gamma}{\alpha_M}$):

$$
\begin{aligned}
q_{it} &= \frac{\gamma}{\hat{\beta}} \frac{s_{Lit}}{s_{Mit}} (l_{it} - k_{it}) + \frac{\gamma}{\hat{\beta}} (m_{it} - k_{it}) + \gamma k_{it} \\
&+ \hat{\phi}_a \frac{\gamma}{\hat{\beta}} LHS_{it-1} - \hat{\phi}_a \gamma k_{it-1} - \hat{\phi}_a \left(r_{it-1} \frac{\gamma}{\hat{\beta} s_{Mit-1}} - q_{it-1} \right) + \nu_{ait}.
\end{aligned}
$$

and estimate the only useful parameter left (γ) by building on the moment condition $E\{\nu_{ait} k_{it}\} = 0$.

The Model: Estimation

We implement this as a linear regression by writing

$$\overline{LHS}_{it} = b_6 z_{6it} + \nu_{ait} \tag{2}$$

where $\overline{LHS}_{it} = q_{it} - \hat{\phi}_a q_{it-1}$ and
$z_{6it} = \frac{1}{\hat{\beta}} \frac{s_{Lit}}{s_{Mit}} (l_{it} - k_{it}) + \frac{1}{\hat{\beta}} (m_{it} - k_{it}) + k_{it} + \frac{\hat{\phi}_a}{\hat{\beta}} LHS_{it-1} - \hat{\phi}_a k_{it-1} - r_{it-1} \frac{\hat{\phi}_a}{\hat{\beta} s_{Mit-1}}$
at as well as $b_6 = \gamma$ and z_{6it} is instrumented with k_{it}.

The Model: Estimation

Using the estimated $\hat{\beta}$, $\hat{\gamma}$ and $\hat{\alpha}_M = \hat{\gamma} / \hat{\beta}$ (parameters inference can be done with bootstrapping) as well as observables we finally get our three measures of heterogeneity:

$$\hat{a}_{it} = q_{it} - \frac{\hat{\gamma}}{\hat{\beta}} \frac{s_{Lit}}{s_{Mit}} (l_{it} - k_{it}) - \frac{\hat{\gamma}}{\hat{\beta}} (m_{it} - k_{it}) - \hat{\gamma} k_{it}$$

$$\hat{\mu}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}}$$

$$\hat{\lambda}_{it} = \frac{\hat{\gamma}}{\hat{\beta} s_{Mit}} r_{it} - q_{it}.$$

Data: Production

We use firm-level production data for Belgian manufacturing firms.

Prodcom is a monthly survey of industrial production. Eurostat established the survey in order to improve the comparability of production statistics across the EU by the use of a common product nomenclature called Prodcom (8-digit codes based on NACE 4-digits).

Data: Production

We use firm-level production data for Belgian manufacturing firms.

Prodcom is a monthly survey of industrial production. Eurostat established the survey in order to improve the comparability of production statistics across the EU by the use of a common product nomenclature called Prodcom (8-digit codes based on NACE 4-digits).

It covers production of broad sectors C and D of NACE Rev. 1.1 (Mining and quarrying and manufacturing), except for sections 10 (Mining of coal and lignite;), 11 (Extraction of crude petroleum and natural gas) and 23 (Manufacture of coke and refined petroleum products).

Data: Production

Each firm with 20 employees or more or with a revenue greater than 3.5 million Euros in a given year is due to fill the survey: medium-large producers. It covers more than 90% of manufacturing production. Raw data is at the plant level.

Data: Production

Each firm with 20 employees or more or with a revenue greater than 3.5 million Euros in a given year is due to fill the survey: medium-large producers. It covers more than 90% of manufacturing production. Raw data is at the plant level.

Around 7,000 firms a year over the period 1995-2009. Data is organised by product-year-month-firm. We borrow information on quantity (unit of measurement depends on product) and value (euros) of production sold.

We aggregate the data at the firm-year-product level.

Data: Balance sheet and Trade

- Annual accounts from National Bank of Belgium. For this study, we selected those companies that filed a full-format or abbreviated balance sheet between 1996 and 2007 and with at least one full-time equivalent employee.

  - The resulting dataset has been shown to be representative of the Belgian economy.
  - We take information on FTE employment, material costs, capital stock and turnover. More than 15,000 firms per year in manufacturing with complete information.

Data: Balance sheet and Trade

- Annual accounts from National Bank of Belgium. For this study, we selected those companies that filed a full-format or abbreviated balance sheet between 1996 and 2007 and with at least one full-time equivalent employee.
  - The resulting dataset has been shown to be representative of the Belgian economy.
  - We take information on FTE employment, material costs, capital stock and turnover. More than 15,000 firms per year in manufacturing with complete information.

- Standard EU-type micro trade data at the product-country-firm-month level over the period 1995-2008 with different rules for EU and non-EU trade.
  - We borrow information on firm export status.

Sample

- We have applied various checks and cleaning to the data. ▸ Sample

Sample

- We have applied various checks and cleaning to the data. [▸ Sample]
- We do not deal with multi-product firms in this paper. However we could, following the methodologies described in De Loecker (2011) and De Loecker et al. (2014), allow for multi-product firms.

Sample

- We have applied various checks and cleaning to the data. ▸ Sample

- We do not deal with multi-product firms in this paper. However we could, following the methodologies described in De Loecker (2011) and De Loecker et al. (2014), allow for multi-product firms.

- We end up studying four industries: ▸ Products
  - ▸ NACE 151: "Production, processing and preserving of meat and meat products"
  - ▸ NACE 212: "Manufacture of articles of paper and paperboard"
  - ▸ NACE 266: "Manufacture of articles of concrete, plaster and cement"
  - ▸ NACE 361: "Manufacture of furniture"

- Note that we study "Manufacture of articles of concrete, plaster and cement" and not is not "Ready Mixed Concrete"

Distribution of *a* and λ (centered)

Meat

Paper

Concrete
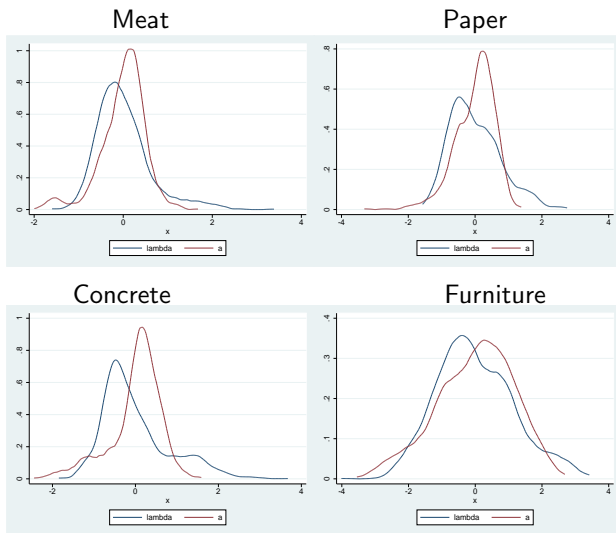
Furniture

Demand shocks at least as dispersed as TFP shocks

Distribution of markups

Meat
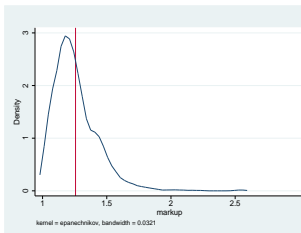
Paper
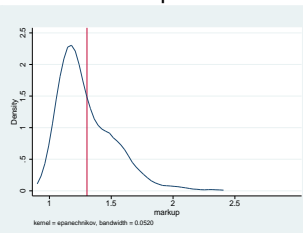
Concrete
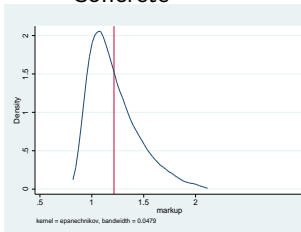
Furniture
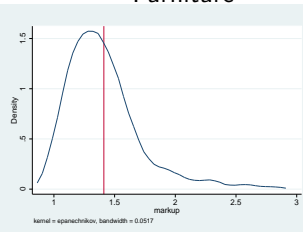
Considerable variation in markups within sectors

Descriptive Statistics: Correlations

	151					212		
	μ	λ	a			μ	λ	a
μ	1				μ	1		
λ	0.417***	1			λ	0.608***	1	
a	0.187***	-0.691***	1		a	-0.0629	-0.663***	1
p	0.0199	0.742***	-0.941***		p	0.213***	0.691***	-0.916***

	266					361		
	μ	λ	a			μ	λ	a
μ	1				μ	1		
λ	0.611***	1			λ	0.0724**	1	
a	-0.115***	-0.767***	1		a	-0.0879***	-0.910***	1
p	0.143***	0.791***	-0.956***		p	0.0772**	0.926***	-0.940***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Productivity shocks a are very strongly and negatively correlated with demand shocks λ in each of the four industries: Nissan vs. Mercedes would be a good metaphor for describing differences among firms within an industry

Nissan vs. Mercedes

Which Plant is better?

Mercedes plant Rastatt
Cars/Employee in 2000: 53

Nissan plant Sunderland
Cars/Employee in 2000: 100

http://www.prnewswire.co.uk/news-releases/nissans-sunderland-car-plant-sets-new-european-productivity-standards-154794285.html

Both plants are profitable and perhaps generate a very similar revenue productivity.

Yet, their business model is quite different: they differentiate themselves in the quality-cost space

Descriptive Statistics: Correlations

		151					212	
	μ	λ	a			μ	λ	a
μ	1				μ	1		
λ	0.417***	1			λ	0.608***	1	
a	0.187***	-0.691***	1		a	-0.0629	-0.663***	1
p	0.0199	0.742***	-0.941***		p	0.213***	0.691***	-0.916***

		266					361	
	μ	λ	a			μ	λ	a
μ	1				μ	1		
λ	0.611***	1			λ	0.0724**	1	
a	-0.115***	-0.767***	1		a	-0.0879***	-0.910***	1
p	0.143***	0.791***	-0.956***		p	0.0772**	0.926***	-0.940***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Markups μ do not seem to be very strongly correlated with demand shocks or productivity shocks. Therefore, this is an important additional dimension of heterogeneity. ▸ more

Descriptive Statistics: Correlations

		151					212	
	μ	λ	a			μ	λ	a
μ	1				μ	1		
λ	0.417***	1			λ	0.608***	1	
a	0.187***	-0.691***	1		a	-0.0629	-0.663***	1
p	0.0199	0.742***	-0.941***		p	0.213***	0.691***	-0.916***

		266					361	
	μ	λ	a			μ	λ	a
μ	1				μ	1		
λ	0.611***	1			λ	0.0724**	1	
a	-0.115***	-0.767***	1		a	-0.0879***	-0.910***	1
p	0.143***	0.791***	-0.956***		p	0.0772**	0.926***	-0.940***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

More productive (Higher quality) firms charge lower (higher) prices.

Predictive power: Quantity

Regression of log quantity on a, μ, λ and capital k

Industry	151	212	266	361
a	1.828***	1.074***	1.36***	.5458***
	(.1563)	(.1975)	(.102)	(.0676)
λ	.9423***	.5549**	.7749***	-.3654***
	(.1543)	(.1724)	(.1002)	(.0665)
μ	-4.388***	-1.958***	-1.881***	-.7247***
	(.4769)	(.4129)	(.2218)	(.0991)
k	.5814***	.7576***	.4271***	.6378***
	(.0223)	(.029)	(.0198)	(.0217)
# Obs	1235	770	1402	1566
R^2	.6477	.7426	.5734	.6887

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Predictive power: Price

Regression of log price on a, μ, λ and capital k

Industry	151	212	266	361
a	-.8891***	-.6858***	-.6195***	-.4877***
	(.0364)	(.0571)	(.0243)	(.0284)
λ	.0692*	.2005***	.286***	.48***
	(.0346)	(.0508)	(.0235)	(.0268)
μ	.4421***	-.0371	-.4334***	-.1729***
	(.0881)	(.1275)	(.0564)	(.0513)
k	-.0729***	-.1229***	-.0674***	-.1351***
	(.003)	(.0045)	(.0031)	(.0071)
# Obs	1235	770	1402	1566
R^2	.9496	.9357	.9415	.932

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Correlation of revenue TFP with a, λ and μ

Revenue TFP is a mixture of the three dimensions of heterogeneity

Olley-Pakes TFP revenue based regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	.4062***	.3995***	.6407***	.6387***
	(.011)	(.0124)	(.0101)	(.0079)
λ	.3678***	.461***	.821***	.6581***
	(.011)	(.0111)	(.0095)	(.0077)
μ	.4246***	.4022***	.1584**	.541***
	(.0282)	(.0283)	(.0214)	(.0094)
# Obs	1235	770	1402	1566
R^2	0.476	0.496	0.447	0.366

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Correlation of revenue TFP with a, λ and μ

Revenue TFP is a mixture of the three dimensions of heterogeneity

FHS TFP revenue based regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	.254**	.1858	.3797***	.2327**
	(.0155)	(.0217)	(.0205)	(.0098)
λ	.2235*	.2986**	.5891***	.2656**
	(.0156)	(.0184)	(.0194)	(.0097)
μ	.2115**	.2716***	.0241	.4876***
	(.044)	(.047)	(.0468)	(.0127)
# Obs	1235	770	1402	1566
R^2	0.159	0.223	0.168	0.250

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Correlation of revenue TFP with a, λ and μ

Revenue TFP is a mixture of the three dimensions of heterogeneity

DLW TFP revenue based regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	1.236***	.9342***	.9488***	.9733***
	(.0197)	(.0305)	(.0171)	(.0167)
λ	1.561***	1.448***	1.525***	1.063***
	(.02)	(.0265)	(.0183)	(.0158)
μ	-.6635***	-.485***	-.279***	-.2395***
	(.0514)	(.063)	(.0427)	(.0226)
# Obs	1233	769	1402	1561
R^2	0.558	0.619	0.639	0.263

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Correlation of revenue TFP with a, λ and μ

Revenue TFP is a mixture of the three dimensions of heterogeneity

OLS TFP revenue based regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	.4153***	.3812***	.6245***	.6486***
	(.0106)	(.0109)	(.0102)	(.0077)
λ	.3693***	.4339***	.783***	.6583***
	(.0107)	(.0093)	(.0095)	(.0072)
μ	.4255***	.4519***	.1813***	.572***
	(.0284)	(.0234)	(.0232)	(.0085)
# Obs	1235	770	1402	1566
R^2	0.464	0.523	0.429	0.392

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Comparison with other methodologies

▶ Comparison

Export Status: what we are used to

It is a stylized fact that exporters are, on average, more productive than non-exporters. Evidence comes from many datasets and countries and is based on standard revenue-based measures of productivity.

Export Status: what we are used to

It is a stylized fact that exporters are, on average, more productive than non-exporters. Evidence comes from many datasets and countries and is based on standard revenue-based measures of productivity.

Our data is no exception to such stylized fact. Consider for example export status of a firm regressed on its OP revenue-based TFP or DLW revenue-based TFP

Export Status: what we are used to

Export Status regressed on OP revenue-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
OP TFP Revenue	.4428***	.3651***	.2075***	.4219***
	(.0128)	(.0202)	(.0232)	(.0153)
# Obs	1235	770	1402	1566
R^2	0.223	0.161	0.0512	0.206

Export Status regressed on DLW revenue-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
DLW TFP revenue	.4249***	.4094***	.4072***	.4378***
	(.0705)	(.0603)	(.0533)	(.0319)
# Obs	1233	769	1402	1561
R^2	0.209	0.196	0.172	0.219

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Export Status: what we ARE NOT are used to

Consider now export status of a firm regressed on quantity-based TFP:

Export Status: what we ARE NOT are used to

Consider now export status of a firm regressed on quantity-based TFP:

Export Status regressed on OP quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
OP TFP quantity	.3646***	.2247***	.0359	.2706***
	(.0134)	(.0172)	(.0164)	(.0079)
# Obs	1235	770	1402	1566
R^2	0.161	0.0804	0.0105	0.102

Export Status regressed on DLW quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
DLW TFP quantity	.2649***	.2572***	.0665*	.3248***
	(.0256)	(.0243)	(.0215)	(.0083)
# Obs	1233	769	1402	1561
R^2	0.0995	0.0961	0.0136	0.134

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Export Status: what we ARE NOT are used to

Consider now export status of a firm regressed on quantity-based TFP:

Export Status regressed on OP quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
OP TFP quantity	.3646***	.2247***	.0359	.2706***
	(.0134)	(.0172)	(.0164)	(.0079)
# Obs	1235	770	1402	1566
R^2	0.161	0.0804	0.0105	0.102

Export Status regressed on DLW quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
DLW TFP quantity	.2649***	.2572***	.0665*	.3248***
	(.0256)	(.0243)	(.0215)	(.0083)
# Obs	1233	769	1402	1561
R^2	0.0995	0.0961	0.0136	0.134

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As one can notice the positive relationship between export status and productivity still holds.

Export Status: what we ARE NOT are used to

Our framework allows to go further.

Export Status: what we ARE NOT are used to

Our framework allows to go further. Consider now export status of a firm regressed on a, λ and μ:

Export Status regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	.5184***	.3714***	.4297***	.108
	(.0523)	(.0388)	(.0407)	(.0243)
λ	.6062***	.6067***	.7451***	.0205
	(.0481)	(.0364)	(.0402)	(.0244)
μ	-.4762***	-.3782***	-.2456***	-.221***
	(.1321)	(.1027)	(.0889)	(.0393)
# Obs	1235	770	1402	1566
R^2	0.126	0.119	0.117	0.0889

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Export Status: what we ARE NOT are used to

Our framework allows to go further. Consider now export status of a firm regressed on a, λ and μ:

Export Status regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	.5184***	.3714***	.4297***	.108
	(.0523)	(.0388)	(.0407)	(.0243)
λ	.6062***	.6067***	.7451***	.0205
	(.0481)	(.0364)	(.0402)	(.0244)
μ	-.4762***	-.3782***	-.2456***	-.221***
	(.1321)	(.1027)	(.0889)	(.0393)
# Obs	1235	770	1402	1566
R^2	0.126	0.119	0.117	0.0889

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As one can notice demand shocks and markups combined have more explanatory power than productivity.

Firm Size: what we are used to

Larger (in term of employment) firms are typically found to be more productive.

Firm Size: what we are used to

Larger (in term of employment) firms are typically found to be more productive.

Our data is no exception to such stylized fact. Consider for example the log number of employees of a firm regressed on its OP revenue-based TFP or DLW revenue-based TFP:

Firm Size: what we are used to

Log number of employees regressed on OP revenue-based TFP: BETA
COEFFICIENTS

Industry	151	212	266	361
OP TFP Revenue	.5882***	.7237***	.557***	.6863***
	(.036)	(.0523)	(.0456)	(.0383)
# Obs	1235	770	1402	1566
R^2	0.348	0.524	0.316	0.470

Log number of employees regressed on DLW revenue-based TFP: BETA
COEFFICIENTS

Industry	151	212	266	361
DLW TFP revenue	.7855***	.7664***	.7994***	.8514***
	(.1171)	(.107)	(.0789)	(.0505)
# Obs	1233	769	1402	1561
R^2	0.620	0.590	0.640	0.719

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Firm size: what we ARE NOT are used to

Consider now firm size regressed on quantity-based TFP:

Firm size: what we ARE NOT are used to

Consider now firm size regressed on quantity-based TFP:

Log number of employees regressed on OP quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
OP TFP quantity	.353***	.3565***	.2492***	.212***
	(.0314)	(.0487)	(.0386)	(.0153)
# Obs	1235	770	1402	1566
R^2	0.131	0.135	0.0751	0.0461

Log number of employees regressed on DLW quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
DLW TFP quantity	.3285***	.3737***	.1384***	.3854***
	(.0461)	(.0589)	(.0398)	(.0169)
# Obs	1233	769	1402	1561
R^2	0.113	0.148	0.0329	0.149

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Firm size: what we ARE NOT are used to

Consider now firm size regressed on quantity-based TFP:

Log number of employees regressed on OP quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
OP TFP quantity	.353***	.3565***	.2492***	.212***
	(.0314)	(.0487)	(.0386)	(.0153)
# Obs	1235	770	1402	1566
R^2	0.131	0.135	0.0751	0.0461

Log number of employees regressed on DLW quantity-based TFP: BETA COEFFICIENTS

Industry	151	212	266	361
DLW TFP quantity	.3285***	.3737***	.1384***	.3854***
	(.0461)	(.0589)	(.0398)	(.0169)
# Obs	1233	769	1402	1561
R^2	0.113	0.148	0.0329	0.149

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As one can notice the positive relationship between firm size and productivity still holds.

Firm Size: what we ARE NOT are used to

Our framework allows to go further.

Firm Size: what we ARE NOT are used to

Our framework allows to go further.Consider now log number of employees of a firm regressed on a, λ and μ:

Log number of employees regressed on a, λ and μ: BETA COEFFICIENTS

Industry	151	212	266	361
a	1.11***	1.021***	.9931***	.341***
	(.1236)	(.1523)	(.0764)	(.0427)
λ	.7612***	.4728***	.4961***	.2496***
	(.1339)	(.1643)	(.0752)	(.0439)
μ	-.5233***	-.5128***	-.2275***	-.2184***
	(.275)	(.3911)	(.1655)	(.0636)
# Obs	1235	770	1402	1566
R^2	0.291	0.290	0.289	0.0708

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Firm Size: what we ARE NOT are used to

Our framework allows to go further.Consider now log number of employees of a firm regressed on a, λ and μ:

Log number of employees regressed on a, λ and μ: BETA COEFFICIENTS

| Industry	151	212	266	361
a	1.11***	1.021***	.9931***	.341***
	(.1236)	(.1523)	(.0764)	(.0427)
λ	.7612***	.4728***	.4961***	.2496***
	(.1339)	(.1643)	(.0752)	(.0439)
μ	-.5233***	-.5128***	-.2275***	-.2184***
	(.275)	(.3911)	(.1655)	(.0636)
# Obs	1235	770	1402	1566
R^2	0.291	0.290	0.289	0.0708

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As one can notice demand shocks and markups combined have similar explanatory power to productivity.

Conclusions

- We provide a framework simultaneously allowing for heterogeneity in productivity, markups and demand across firms while leaving the correlation among the three unrestricted.

- We use production data on Belgian firms to quantify our model.

- We are able to unravel standard measures of revenue productivity into 3 components. This is important at different levels:

  1. **At the micro level:** it makes a huge difference to know that some firms or industries lack in competitiveness because of poor physical TFP (due for example to low expenditure in process R&D) or poor product quality (due for example to low expenditure in product R&D).

  2. **At the macro level:** It allows looking at aggregate revenue productivity cycles, like for example the severe downturn of UK aggregate revenue productivity since the financial crisis, not only in terms of changes in some underlying production capacity of the economy but also as changes in markups and/or consumers' appreciation of firms' products.

How Important is Demand Heterogeneity? Plot of Log Price and Log Quantity
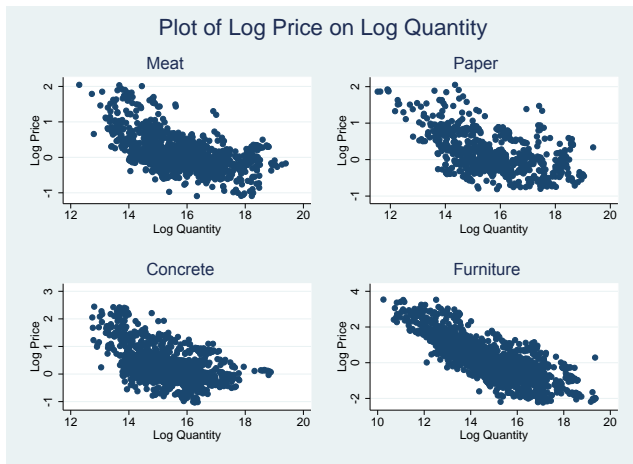
Plot of Log Price on Log Quantity

The Model: Preferences

Consider starting from direct utility and suppose a representative consumer maximises a differentiable utility function $U(.)$ subject to budget B_t:

$$\max_{Q_t} \left\{ U\left(\tilde{Q}_t \right) \right\} \text{ s.t. } \int_i P_{it} Q_{it} \mathrm{d}i - B_t$$

where $\tilde{Q}_t$ is a vector of elements $\Lambda_{it} Q_{it}$. Λ_{it} is a demand shock.

The Model: Preferences

Consider starting from direct utility and suppose a representative consumer maximises a differentiable utility function $U(.)$ subject to budget B_t:

$$\max_{Q_t} \left\{ U\left(\tilde{Q}_t\right) \right\} \text{ s.t. } \int_i P_{it} Q_{it} \mathrm{d}i - B_t$$

where $\tilde{Q}_t$ is a vector of elements $\Lambda_{it} Q_{it}$. Λ_{it} is a demand shock. Now use small case for logs (for example $\lambda_{it} = \ln \Lambda_{it}$) and define:

- Elasticity of demand: $\eta_{it} \equiv -\frac{\partial q_{it}}{\partial p_{it}}$
- Markup: $\mu_{it} \equiv \frac{P_{it}}{MC_{it}} = \frac{\eta_{it}}{\eta_{it}-1}$

Where the relationship between the markup and the elasticity of demand comes from the monopolistic competition assumption (2nd departure from DLW).

The Model: Preferences

From first-order conditions we immediately get:

$$\frac{\partial p_{it}}{\partial q_{it}} = -\frac{1}{\eta_{it}}$$

and

$$\frac{\partial p_{it}}{\partial \lambda_{it}} = 1 - \frac{1}{\eta_{it}} = \frac{1}{\mu_{it}}$$

i.e. the elasticity of prices with respect to output quantity differs from the elasticity of prices w.r.t to the demand shock Λ_{it} by one.

The Model: Preferences

From first-order conditions we immediately get:

$$\frac{\partial p_{it}}{\partial q_{it}} = -\frac{1}{\eta_{it}}$$

and

$$\frac{\partial p_{it}}{\partial \lambda_{it}} = 1 - \frac{1}{\eta_{it}} = \frac{1}{\mu_{it}}$$

i.e. the elasticity of prices with respect to output quantity differs from the elasticity of prices w.r.t to the demand shock Λ_{it} by one. This is a key property as it allows us to rewrite changes in log revenue $r_{it}=q_{it} + p_{it}$ as:

$$\Delta r_{it} \simeq \frac{1}{\mu_{it}} \Delta \tilde{q}_{it} = \frac{1}{\mu_{it}} \Delta \left(q_{it} + \lambda_{it} \right) \tag{3}$$

The Model: Preferences

A convenient and flexible case is the Generalized CES: Spence (1976)

$$U(\tilde{Q}_t) = \int_{i \in I_t} a_{it} \left(\tilde{Q}_{it} \right)^{b_{it}} \mathrm{d}i = \int_{i \in I_t} a_{it} \Lambda_{it}^{b_{it}} \left(Q_{it} \right)^{b_{it}} \mathrm{d}i$$

where $b_{it} = 1 - \frac{1}{\eta_{it}}$.

The Model: Preferences

A convenient and flexible case is the Generalized CES: Spence (1976)

$$U(\tilde{Q}_t) = \int_{i \in I_t} a_{it} \left(\tilde{Q}_{it} \right)^{b_{it}} \mathrm{d}i = \int_{i \in I_t} a_{it} \Lambda_{it}^{b_{it}} \left(Q_{it} \right)^{b_{it}} \mathrm{d}i$$

where $b_{it} = 1 - \frac{1}{\eta_{it}}$.

If we further impose $a_{it} = \frac{1}{1 - \frac{1}{\eta_{it}}}$ not only (3) holds but we actually have

$r_{it} = \frac{1}{\mu_{it}} \left(q_{it} + \lambda_{it} \right)$. **This is our benchmark case**.

The Model: Preferences

- In sum for any preference structure that can be used to model monopolistic competition, and that can be conveniently described by a direct utility we can, starting from the baseline formulation $U(Q_t)$, introduce demand shocks in such a way that (3) is satisfied.

The Model: Preferences

- In sum for any preference structure that can be used to model monopolistic competition, and that can be conveniently described by a direct utility we can, starting from the baseline formulation $U(Q_t)$, introduce demand shocks in such a way that (3) is satisfied.

- In this setting demand shocks Λ_{it} have a quality interpretation.

The Model: Preferences

- In sum for any preference structure that can be used to model monopolistic competition, and that can be conveniently described by a direct utility we can, starting from the baseline formulation $U(Q_t)$, introduce demand shocks in such a way that (3) is satisfied.

- In this setting demand shocks Λ_{it} have a quality interpretation.

- For some specific preferences (Ex. Gaussian utility) we can modify our procedure to get exact formulas (like in the Generalized CES case with $a_{it} = \frac{1}{1 - \frac{1}{\eta_{it}}}$) rather than an approximation.

The Model: Preferences

- In sum for any preference structure that can be used to model monopolistic competition, and that can be conveniently described by a direct utility we can, starting from the baseline formulation $U(Q_t)$, introduce demand shocks in such a way that (3) is satisfied.
- In this setting demand shocks Λ_{it} have a quality interpretation.
- For some specific preferences (Ex. Gaussian utility) we can modify our procedure to get exact formulas (like in the Generalized CES case with $a_{it} = \frac{1}{1 - \frac{1}{\eta_{it}}}$) rather than an approximation.
- As for preferences that do not fall within our class (Generalised Quadratic Utility, Di Comite et al. (2014), Translog Preferences, various Feenstra papers, etc.) we can start from demand and work out the constraints that need to be imposed.

▸ GQU

▸ key property

The Model: Preferences

Consider the Generalised Quadratic Utility: Di Comite et al. (2014)

$$U(Q_t) = \int_{i \in I_t} a_{it} Q(it) \mathrm{d}i - \frac{1}{2} \int_{i \in I_t} b_{it} \left[Q(it)\right]^2 \mathrm{d}i - \frac{c_{it}}{2} \left[\int_{i \in I_t} Q(it) \mathrm{d}i\right]^2 + Q_{0t}$$

where Q_{0t} is a numéraire good.

After deriving the inverse demand function one can impose constraints such that $\frac{\partial p_{it}}{\partial \lambda_{it}} = 1 + \frac{\partial p_{it}}{\partial q_{it}}$. This is achieved by imposing $a_{it} = a_1 \Lambda_{it}$, $b_{it} = b_1 \left(\Lambda_{it}\right)^2$ and $c_{it} = c_1 \Lambda_{it}$, where a_1, b_1 and c_1 are positive constants.

▸ key property

Sector 151: Meat and Meat Products

code 15131215: Sausages not of liver

code 15131225: Preparations of animal liver (incl. pates & pastes other than in sausage) food preparations containing >20% of meat (excl. sausages/homogenized preparations, of goose or duck)

code 15131259: Preparations of pork (incl. mixtures; fats of any kind or origin, excl. prepared dishes, sausages and similar products, pates and pastes, homogenized preparations)

Sector 212: Articles of Paper

code 21231230: Envelopes of paper or paperboard

code 21241190: Wallpaper and other wall coverings; window transparencies of paper, n.e.c.

Sector 266 : Articles of Concrete

Code 26611130: Building blocks and bricks of cement; concrete or artificial stone

Code 26611200: Prefabricated structural components for building, of cement

Sector 361 : Furniture

Code 36111250:Upholstered seats with wooden frames (incl. three piece suites) (excl. swivel seats)

Code 36111290: Non-upholstered seats with wooden frames (excl. swivel seats)

▸ aggregation   ▸ back

Sample

- We focus on the period 1996-2007 for which all of our data is available and during which there has not been any major change in data collection and data nomenclatures (NACE codes, Prodcom codes, etc.).

Sample

- We focus on the period 1996-2007 for which all of our data is available and during which there has not been any major change in data collection and data nomenclatures (NACE codes, Prodcom codes, etc.).
- We match the three datasets by the unique firm VAT identifier and:
  - Consider only firm-year observations for which the value and quantity of production for all products (8-digit) are recorded
  - Consider only firm-year observations for which employment, materials, sales and capital are available
  - Aggregate production data at the 3 digit-unit of measurement level
    - ▸ aggregation
  - Create for each firm-year the production value shares of its different 3 digit-unit products and keep a firm-year couple only if > 95% of production value is within a given 3 digit-unit: Single-product firms
  - Apply small trimmings (1% up and down) based on capital intensity, share of intermediates in revenues and unit prices
  - Consider only 3-digit sectors with more than 80 firms in each year
    - ▸ back

Aggregation

Suppose firm i produces many products indexed by j. Further suppose that log quantity is $q_{ij}=q_i + s_j^q$ and that log demand shock is $\lambda_{ij}=\lambda_i + s_j^\lambda$ where s_j^q and s_j^λ are constant across firms.

Aggregation

Suppose firm i produces many products indexed by j. Further suppose that log quantity is $q_{ij} = q_i + s_j^q$ and that log demand shock is $\lambda_{ij} = \lambda_i + s_j^\lambda$ where s_j^q and s_j^λ are constant across firms.

Now impose $\mu_{ij} = \mu_i$. We thus get:

$$r_{ij} = p_{ij} + q_{ij} = \frac{1}{\mu_i}\left(q_{ij} + \lambda_{ij}\right) = \frac{1}{\mu_i}\left(s_j + q_i + \lambda_i\right) = \frac{1}{\mu_i}\left(\tilde{q}_{ij} + \lambda_i\right),$$

where $s_j = s_j^q + s_j^\lambda$ and $\tilde{q}_{ij} = s_j + q_i$.

Aggregation

Suppose firm i produces many products indexed by j. Further suppose that log quantity is $q_{ij} = q_i + s_j^q$ and that log demand shock is $\lambda_{ij} = \lambda_i + s_j^\lambda$ where s_j^q and s_j^λ are constant across firms.

Now impose $\mu_{ij} = \mu_i$. We thus get:

$$r_{ij} = p_{ij} + q_{ij} = \frac{1}{\mu_i}\left(q_{ij} + \lambda_{ij}\right) = \frac{1}{\mu_i}\left(s_j + q_i + \lambda_i\right) = \frac{1}{\mu_i}\left(\tilde{q}_{ij} + \lambda_i\right),$$

where $s_j = s_j^q + s_j^\lambda$ and $\tilde{q}_{ij} = s_j + q_i$.

Everything works as if the firm was producing identical products, i.e., having the same productivity, demand and markups shocks as well as technology constraint, in different quantities $\tilde{q}_{ij}$.

Aggregation

The problem is that q_{ij} is directly observable in our data while $\tilde{q}_{ij}$ is not.

Aggregation

The problem is that q_{ij} is directly observable in our data while $\tilde{q}_{ij}$ is not. Yet, from the above equation we get:

$$p_{ij} = r_{ij} - q_{ij} = \frac{1}{\mu_i}\left(\tilde{q}_{ij} + \lambda_i\right) - q_i - s_j^q = \frac{1}{\mu_i}\left(q_i + \lambda_i\right) - q_i + \frac{1}{\mu_i}s_j - s_j^q.$$

Aggregation

The problem is that q_{ij} is directly observable in our data while $\tilde{q}_{ij}$ is not. Yet, from the above equation we get:

$$
p_{ij} = r_{ij} - q_{ij} = \frac{1}{\mu_i}\left(\tilde{q}_{ij} + \lambda_i\right) - q_i - s_j^q = \frac{1}{\mu_i}\left(q_i + \lambda_i\right) - q_i + \frac{1}{\mu_i}s_j - s_j^q.
$$

We finally posit $\mathbb{E}\left[p_{ij}|i \in I^j\right] = a + bs_j - s_j^q$ where I^j is the set of firms i producing product j.

This amounts to assume that the distributions of productivity, markups and demand shocks corresponding to firms selling a given product are similar across the 8-digit products belonging to a given industry.

Aggregation

The above assumption implies that, by multiplying the average (across firms within a product) log price p_{ij} observed in the data by the observed q_{ij} we get a monotonous transformation of $\tilde{q}_{ij}$:

$$\mathbb{E}\left[p_{ij}|i \in I^j\right] q_{ij} = a + bs_j + q_i.$$

that we can use to quantify parameters. Note that using a monotonous transformation of $\tilde{q}_{ij}$ rather than $\tilde{q}_{ij}$ is irrelevant for the purpose of our model given our extensive use of linear regressions.

▸ back

More on Markups

Regression of Markups on a, μ, λ and capital k

Industry	151	212	266	361
a	.3369***	.2579***	.332***	.0155
	(.015)	(.0314)	(.0141)	(.0356)
λ	.3259***	.3297***	.374***	.0369
	(.0128)	(.014)	(.0089)	(.0355)
k	-.0368***	-.0447***	-.0259***	-.0801***
	(.0044)	(.0055)	(.005)	(.006)
# Obs	1235	770	1402	1566
R^2	.6625	.6491	.6961	.1112

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

▸ back

More on Markups

Correlation with DLW markups is one by construction. Only level can be different.

A substantial difference between the two methodologies arises when unobservable (to the firm) productivity shocks enter into the analysis. When applying DLW correction in our data we get a (significant at the 1%) correlation (across all sectors while demeaning) between the two sets of markups of only 0.0633.

The difference is clearly substantial and calls for a serious evaluation of both the importance of productivity shocks unobservable to the firm as well as the capacity of the proxy variable approach to separate observable and unobservable (to the firm) shocks.

More on Productivity

There is considerable difference between revenue-based and quantity-based TFP:

- DLW, quantity and revenue based: 0.380***
- OP, quantity and revenue based: 0.0929***
- FHS, quantity and revenue based: 0.0863***
- OLS, quantity and revenue based: 0.0921***
  *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Second, the correlations (across all sectors while demeaning) between our quantity TFP measure a and quantity TFP measures computed with other methods are:

- DLW, quantity based: 0.866***
- OP, quantity based: 0.948***
- FHS, quantity based: 0.935***
- OLS, quantity based: 0.948***
  *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Therefore, the key message is that having quantity TFP is the key thing.

More on Demand

In light of our framework, FHS approach is problematic for at least two reasons:

1. Markups are heterogeneous across firms: this means that the log price coefficient in their regression should be firm-specific. Within our framework we do not need to estimate those firm-specific coefficients because, based on our assumptions, they equal $-\eta_{it}$.

2. Demand shocks are strongly correlated with productivity shocks: this means that their IV strategy would not work in our data. Within our framework we do not need to take a stand on the correlation between demand and productivity shocks.

More on Demand

Correlation between λ and FHS demand shocks

Industry	correlation
151	0.294***
212	0.414***
266	0.238***
361	0.231***

*** p<0.01, ** p<0.05, * p<0.1

Correlation between our residual demand shocks and FHS demand shocks

Industry	correlation
151	0.217***
212	0.299***
266	0.058
361	0.162***

*** p<0.01, ** p<0.05, * p<0.1

▸ back

Plot of λ and FHS demand shocks

Plot of our residual demand shocks and FHS demand shocks

Plot of Residual demand shock on FHS demand shock

`back`