Unraveling Firms: Demand, Productivity and Markups Heterogeneity

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- 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.

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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.

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  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.

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

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Links with firm size and export status

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 (the dynamic input) is predetermined in t. Consequently, firms are dealing with the following short run cost minimization problem

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

where A_{it} is firm TFP.

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

The Model: Preferences

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We impose:

$$\frac{\partial r_{it}}{\partial \lambda_{it}} = \frac{1}{\mu_{it}}$$

which implies ($\tilde{q}_{it} = q_{it} + \lambda_{it}$):

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

The Model: Preferences

There are various ways of getting $\frac{\partial r_{it}}{\partial \lambda_{it}} = \frac{1}{\mu_{it}}$:

1. Start from direct utility and work with $\tilde{Q}_{it} = Q_{it}\Lambda_{it}$
   For example:

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

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Our framework can be applied to discrete/continuous choice models and oligopolistic competition

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

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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:

$$a_{it} = \phi_a a_{it-1} + \nu_{ait}$$
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- 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 of materials and s_{Mit} is the share of expenditure on materials in revenue.

The Model: Estimation

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Optimal expenditures in materials m_{it} and labour l_{it} can be expressed as a function of the predetermined input (capital) and the 3 state variables (productivity, markups and demand shocks in t).

We show monotonicity with respect to a_{it} DOES NOT generally apply when there are increasing returns to scale. So even if suitable proxies for μ_{it} and λ_{it} were available one COULD NOT invert the expenditure function and use a two-step proxy variable approach to estimate TFP.

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Both output prices and market shares will in general depend on the full set of variables (k_{it}, a_{it}, λ_{it} and μ_{it}) and it is not guaranteed that:

- one can express m_{it} as a deterministic function of capital, productivity, output price and market share;
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In the case of the Generalized CES the revenue equation $r_{it} = \frac{1}{\mu_{it}}(q_{it} + \lambda_{it})$ can be rewritten as:

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

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 $z_{1it}=k_{it}$, $z_{2it}=LHS_{it-1}$, $z_{3it}=k_{it-1}$, $z_{4it}=\frac{r_{it-1}}{s_{Mit-1}}$, $z_{5it}=q_{it-1}$, $u_{it}=\frac{1}{\alpha_M}\left(\nu_{ait}+\nu_{\lambda it}\right)$ 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 $b_5=-\left(\phi_\lambda-\phi_a\right)\frac{1}{\alpha_M}$.

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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: $\hat{\beta}\equiv\widehat{\frac{\gamma}{\alpha_M}}$ and $\hat{\phi}_a$.

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:

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

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

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).

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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).

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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.

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  - 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.

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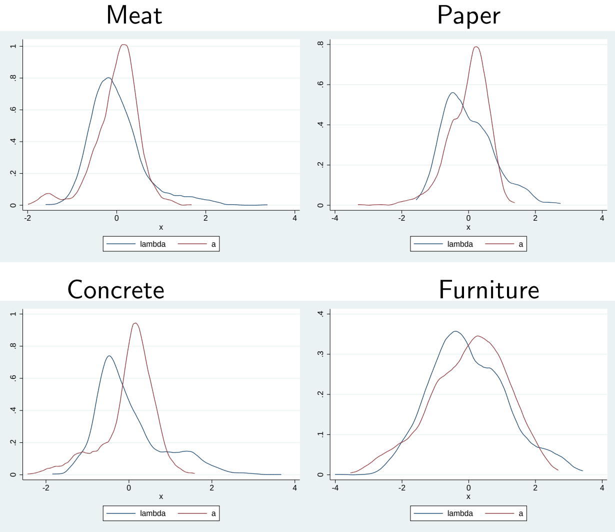
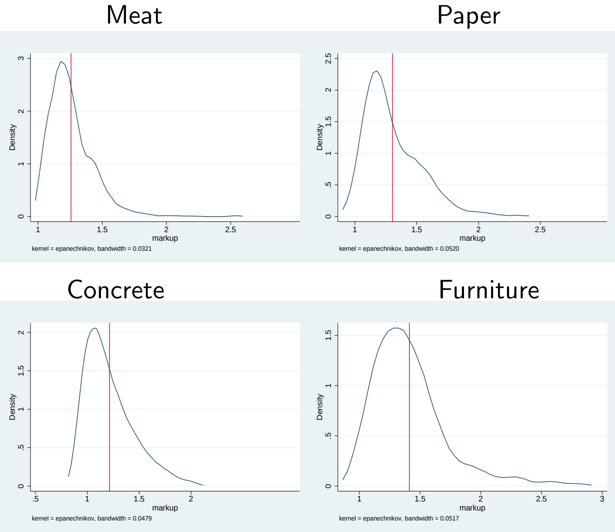
- We do not deal with multi-product firms in this paper. However we provide a generalisation of our model and procedure that allows for multi-product firms.
- We end up studying four industries: ▸ Products
  - NACE 151: "Production, processing and preserving of meat and meat products"
  - NACE 212: "Manufacture 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)



Demand shocks at least as dispersed as TFP shocks

Distribution of markups



Considerable variation in markups within sectors

Descriptive Statistics: Correlations

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

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

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

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

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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

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p	0.143***	0.791***	-0.956***	0.0772**	0.926***	-0.940***

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

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

This makes sense!

Correlations across time

Numerous studies on productivity report a high degree of persistency across time while Foster et al., 2008 document a similar behavior for their measure of demand shocks.

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Remember we have assumed a Markov process for productivity and demand.

Correlations across time

Regression of a, λ and μ on their time lag

Industry	151	212	266	361
		a		
Lag a	.9175***	.9477***	.9138***	.8372***
	(.0224)	(.0211)	(.0172)	(.0202)
R^2	.8535	.8925	.8825	.7342
		λ		
Lag λ	.8736***	.8944***	.9169***	.8231***
	(.0238)	(.0246)	(.0204)	(.0212)
R^2	.8135	.8058	.8396	.7096
		μ		
Lag μ	.8013***	.7949***	.8493***	.8743***
	(.0309)	(.0264)	(.019)	(.0225)
R^2	.6869	.7244	.7381	.7338

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

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

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

Decomposing revenue TFP

Revenue TFP could be defined in our framework as $TFP_{it}^{R} \equiv r_{it} - \bar{q}_{it}$ where $\bar{q}_{it} = \alpha_L (l_{it} - k_{it}) + \alpha_M (m_{it} - k_{it}) + \gamma k_{it}$.

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By substituting and simplifying we get:

$$TFP_{it}^{R} = \frac{1}{\mu_{it}} (a_{it} + \lambda_{it}) + \frac{1 - \mu_{it}}{\mu_{it}} \bar{q}_{it}$$

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By substituting and simplifying we get:

$$TFP_{it}^{R} = \frac{1}{\mu_{it}} (a_{it} + \lambda_{it}) + \frac{1 - \mu_{it}}{\mu_{it}} \bar{q}_{it}$$

So revenue productivity is a function of a, λ, μ and production scale.

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

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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

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OP TFP quantity	.3646***	.2247***	.0359	.2706***
	(.0134)	(.0172)	(.0164)	(.0079)
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	(.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.

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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

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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.

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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

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

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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

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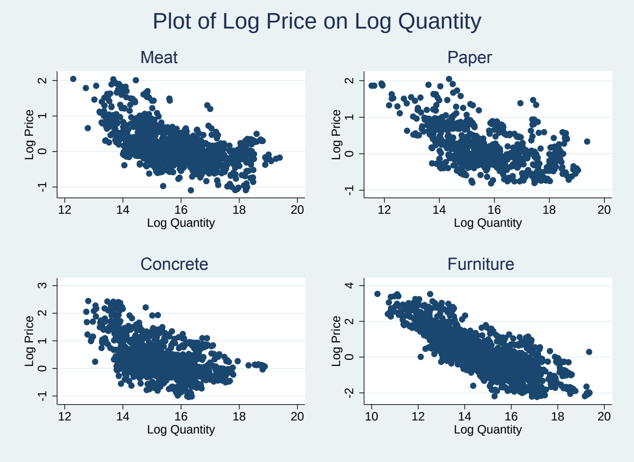
As one can notice demand shocks and markups combined have similar explanatory power to productivity.

Conclusions

- We provide a framework allowing to simultaneously retrieve 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



back

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.

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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 assuming monopolistic competition.

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.

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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:

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

The Model: Preferences

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

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

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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 for which the direct utility function exists we can, starting from the baseline formulation $U(Q_t)$, introduce demand shocks in such a way that (3) is satisfied.

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- 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) 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

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- 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
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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.

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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 $\tilde{q}_{ij} = s_j + q_i$.

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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

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

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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.

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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.

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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

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

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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***

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

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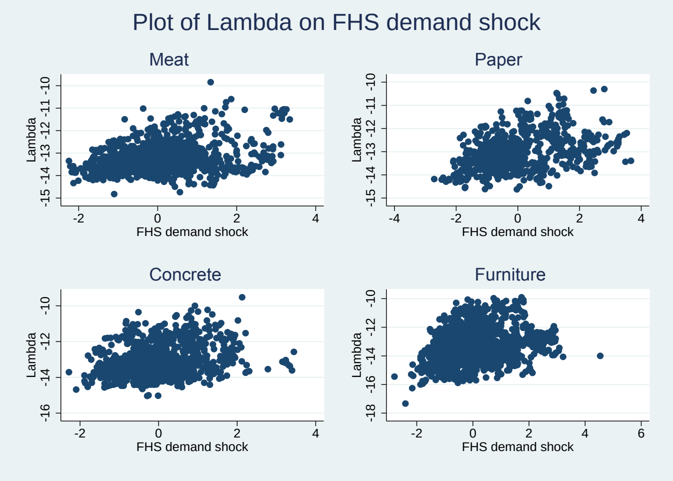
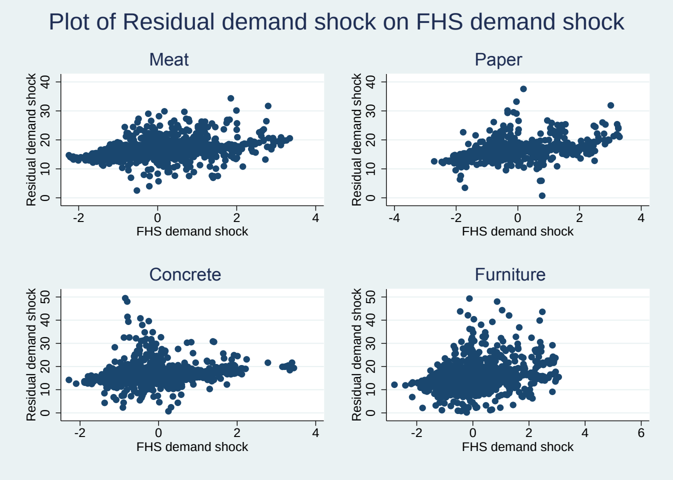
Plot of λ and FHS demand shocks



Plot of our residual demand shocks and FHS demand shocks



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