Biased Technological Change and Employment

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Introduction

- Technological change can increase productivity of all factors or be biased towards a specific factor.

- In fact literature on economic growth shows that steady-state growth needs labor augmenting productivity.

- In practice: scarce evidence and doubts/fear of the employment consequences of labor saving technical change.

- Macro model trends are not very convincing given firms' heterogeneity (from Blanchard, 1997, to McAdam and William, 2008; but see Oberfield and Raval, 2014).

- Micro models systematically specify productivity as Hicks neutral (from Olley and Pakes, 1996, to Gandhi, Rivers and Navarro, 2014).

- The paper "Measuring the Bias of Technological Change," Doraszelski and Jaumandreu (2016), tries to fill a research gap:

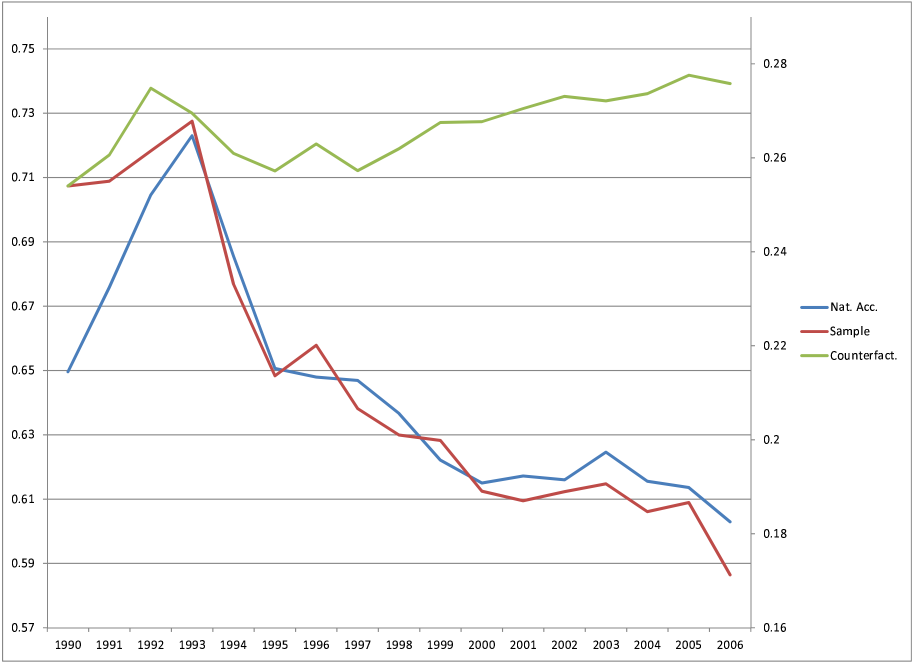
  - Measurement of neutral and biased technological change at the firm level.

  - Characterization of their distributions and relation to R&D.

- Results full of consequences for the evolution of employment (that the paper doesn't develop explicitly).

- An outcome that summarizes results and indicate the importance for employment is the "counterfactual" included in the latest version:

  - Biased technological change explains the entire fall of the aggregate share of labor in income during the period 1990-2006 as documented by the Spanish National Accounts.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- Some relevant questions:

  - Can biased technological change (in opposition to neutral) be the responsible of job destruction?

  - Can the relative amount of biased change explain differences in the employment growth of countries?

  - What are the implications for economic policy?

- This talk:

  - Will give a positive answer to the first question, but also show that Spanish poor employment performance in Manufacturing cannot be fully explained in this way.

  - Will add a few considerations on how we can try to answer the other questions.

Outline

- Background: Measuring the bias of technological change
- Background: Results of the measurement
- Employment effects of neutral technological change
- Employment effects of biased technological change
- Application: Did technological change destroy jobs in Spanish manufacturing 1990-2006?
- Concluding remarks

Measuring the bias of Technological Change

- A CES production function with labor-augmenting productivity ω_L and Hick-neutral productivity ω_H :

$$Y_{jt} = \gamma\left[\beta_K K_{jt}^{-\frac{1-\sigma}{\sigma}} + \beta_L \left(\exp(\omega_{Ljt})\widetilde{L}_{jt}\right)^{-\frac{1-\sigma}{\sigma}} + \beta_M \widetilde{M}_{jt}^{-\frac{1-\sigma}{\sigma}} \right]^{-\frac{\nu\sigma}{1-\sigma}} \exp(\omega_{Hjt}) \exp(e_{jt}).$$

- Productivity follows endogenous Markov processes shifted by firm's R&D:

$$\omega_{Ljt+1} = E_t[\omega_{Ljt+1}|\omega_{Ljt}, r_{jt}] + \xi_{Ljt+1} = g_{Lt}(\omega_{Ljt}, r_{jt}) + \xi_{Ljt+1},$$
$$\omega_{Hjt+1} = E_t[\omega_{Hjt+1}|\omega_{Hjt}, r_{jt}] + \xi_{Hjt+1} = g_{Ht}(\omega_{Hjt}, r_{jt}) + \xi_{Hjt+1}.$$

- $\widetilde{L}_{jt}$ and $\widetilde{M}_{jt}$ are the result of aggregating two types of workers (permanent and temporary) and two types of materials (in-house and outsourced parts and pieces).

• FOC's allow to develop two equations (in logs):

$$(m_{jt} - l_{jt}) = a + controls - \sigma(p_{Mjt} - w_{jt}) + (1-\sigma)\omega_{Ljt},$$

$$y_{jt} = b - \frac{\nu\sigma}{1-\sigma}\ln\left[\beta_K K_{jt}^{-\frac{1-\sigma}{\sigma}} + \beta_M \frac{1}{\widetilde{S}_{Mjt}} \widetilde{M}_{jt}^{-\frac{1-\sigma}{\sigma}}\right] + \omega_{Hjt} + e_{jt},$$

where L_{jt} and M_{jt} are observed workers and in-house materials, S_{Mjt} is the share of materials in variable cost, the tildes represent that the variables have some controls embedded.

• The controls account for the movements in $m_{jt} - l_{jt}$ due to permanent workers adjustments costs and outsourcing dynamics, according to the firm dynamic model.

• Replacing ω_{Ljt} and ω_{Hjt} by expressions based on the Markov processes and FOC's (an Olley and Pakes, 1996, type of procedure), σ can be estimated in the first equation and β_K, β_M and ν in the second. Estimation by nonlinear GMM allows to recover $\widehat{\omega}_{Ljt}$ and $\widehat{\omega}_{Hjt}$ up to a constant.

Results

- The elasticity of substitution σ turns out to be significantly less that one, so CD is rejected and biased technical change has a separate effect on labor.

- Technological change is biased. Labor increases its efficiency at quite strong rates $\Delta\omega_L$ in most of the industries. Ceteris paribus, labor-augmenting technological change causes output to grow at rates $\varepsilon\Delta\omega_L$, which amount on average 1.5% per year.

- There is also Hicks-neutral technological change, at rates $\Delta\omega_H$, which causes output to grow on average by another 1.5% a year.

- In addition of the standard specification tests, estimation passes well a series of robustness checks:

  - Only a small part of productivity growth can be attributed to the change in skills.

  - Results are robust to purging the wage instrument for variations due to quality of labor.

  - Capital shows no similar capital-augmenting productivity.

Labor-saving and Hicks-neutral productivity

Industry	σ	(s. e.)	$\Delta\omega_L$	$\varepsilon\Delta\omega_L$	$\Delta\omega_H$
1. Metals	0.535	(0.114)	0.091	0.021	0.044
2. Non-met.	0.730	(0.098)	0.146	0.031	0.005
3. Chemical	0.696	(0.102)	0.061	0.016	0.019
4. Machinery	0.607	(0.196)	0.125	0.032	0.041
5. Electrical	0.592	(0.123)	0.216	0.021	0.020
6. Transport	0.798	(0.088)	0.145	0.030	0.042
7. Food	0.616	(0.081)	0.017	0.006	0.001
8. Textile	0.440	(0.186)	0.038	0.009	0.012
9. Furniture	0.438	(0.093)	0.067	0.002	0.021
10. Paper	0.525	(0.088)	0.009	0.012	0.002

The firm-level employment effects of neutral technological change

- A firm produces with the production function

$$Y = F(K, L, M)\exp(\omega_H),$$

where we assume, for simplicity, CRTS and flexibility of capital.

- The assumptions imply the cost function

$$C = c(P_K, W, P_M)\frac{Y}{\exp(\omega_H)},$$

and, by Shephard's Lemma, the demand for labor

$$L = \frac{\partial C}{\partial W} = c_W \frac{Y}{\exp(\omega_H)}.$$

• The firm faces a demand for its differentiated product in a monopolistic competitive market

$$Y = D(P)\exp(\delta),$$

where δ is a demand shifter. The firm maximizes profits, so

$$P = \frac{\eta}{\eta - 1}\frac{c(P_K, W, P_M)}{\exp(\omega_H)}.$$

• Let's explore the effect on L of exogenous changes of ω_H, δ and W (it is straightforward to generalize to more general changes in prices).

• Replace the price in the demand function by its optimal value, plug the demand for output in the expression for L. Log differentiating, we can arrive to the following equation in rates of growth (represented by lowercase letters):

$$l = (\varepsilon_{WW} - \eta\varepsilon_W)w - d\omega_H + \eta d\omega_H + d\delta.$$

- Effects:

    - A negative effect of any wage increase coming from two sources: substitution ($\varepsilon_{WW} < 0$ by concavity of the cost function) and the decrease in demand coming from the impact of wage on marginal cost.

    - A **displacement** effect $-d\omega_H$ coming from the effect of technological change for a given output.

    - A **compensation** effect $\eta d\omega_H$ due to the reduction in marginal cost thanks to technological progress.

    - A **demand** effect $d\delta$ induced by the change in the shifter.

- As η is typically greater than one we expect the **compensation** effect to dominate the **displacement** effect. The **demand** effect can add positive impact of innovations (mainly product, and maybe process).

- The paper by Harrison et al., 2014 (HJMP) and related evidence can be read as a confirmation that these mechanisms work and a trial to quantify them.

The firm-level employment effects of biased technological change

- Let's now assume that the production function is

$$Y = F(K, \exp(\omega_L)L, M)\exp(\omega_H).$$

- Let's call L^* to the efficient amount of work: $L^* = \exp(\omega_L)L$. And let's call W^* to the cost of an efficient unit of labor

$$W^* = \frac{WL}{\exp(\omega_L)L} = \frac{W}{\exp(\omega_L)}.$$

Technological change not only increases the efficiency of labor, also decreases the cost of an efficient unit: $w^* = w - d\omega_L$.

- Keep the rest of assumptions. And let's consider again the effects on L of exogenous changes of $\omega_L, \omega_H, \delta$ and W (it is straightforward to generalize to more general changes in prices).

• It is easy to arrive to the following equation

$$l = (\varepsilon_{WW} - \eta\varepsilon_W)w - \varepsilon_{WW}d\omega_L - d\omega_L + \eta\varepsilon_W d\omega_L - d\omega_H + \eta d\omega_H + d\delta.$$

• Effects:

- There is, as before, a negative effect of any wage increase coming from two sources: substitution and decrease in demand.

- There is now a **positive substitution** effect ($-\varepsilon_{WW} > 0$) of ω_L coming from the decrease in the cost per efficient unit.

-There are now two **displacement** effects and two **compensation** effects. The amount of the compensation effect of labor-augmenting productivity is more moderate (ω_L only affects to marginal cost, and hence price, through the cost of labor).

- There is, as before, a **demand** effect $d\delta$ induced by the change in the shifter.

• Now it is not warranted that the compensation effect of labor-augmenting productivity is going to counterbalance the displacement effect, but the positive substitution effect can help.

Did biased technological change destroy jobs in Spain 1990-2006?

- With the described framework and the numbers of DJ the different effects can be preliminary assessed with a simple exercise.

- Interesting exercise, because employment was stagnant.

- DJ specifies a firm specific elasticity of demand η to control for imperfect competition. Let's take the implicit industry average of η (the inverse of the average estimated markups). We also have estimates of ε_W and ε_{WW}.

- Compensation effects through output, both of labor-saving and Hicksian productivity, are on average quite strong: around 5%.

- Hicksian productivity compensation more than balances displacement, creating a positive impact on employment (around 3%). Labor-saving productivity compensation is not able to counterbalance the displacement effect in all industries but 2 and 10.

- Positive substitution effects of labor-saving productivity are significant (around 2%). Adding the substitution effect of labor-saving productivity reduces considerably the negative impact, but doesn't eliminate it.

- The total effects of technological change are however positive in most of the sectors (only moderately negative in industries 4 and 9).

- The real evolution of employment tended to be worse than the evolution predicted by technological change effects (with the exception of industries 4, 7 and 9). This suggests an important role of the rest of factors impacting employment: prices evolution and the demand shifter.

Compensation through output and net displacement

Industry	η	Compensation		Net displac.	
		$\eta\varepsilon_W\Delta\omega_L$	$\eta\Delta\omega_H$	*LS*	*HN*
1. Metals	2.326	0.049	0.102	-0.042	0.058
2. Non-met.	5.848	0.181	0.029	0.035	0.024
3. Chemical	2.488	0.040	0.047	-0.021	0.028
4. Machinery	1.789	0.057	0.073	-0.068	0.032
5. Electrical	5.236	0.110	0.105	-0.106	0.085
6. Transport	2.165	0.065	0.091	-0.080	0.049
7. Food	2.203	0.013	0.002	-0.004	0.001
8. Textile	2.037	0.018	0.024	-0.002	0.012
9. Furniture	1.852	0.004	0.039	-0.063	0.018
10. Paper	2.012	0.028	0.004	0.019	0.002

Substitution and total effects

Industry	Sustit. $\|\varepsilon_{WW}\|\Delta\omega_L$	*LS* net disp. +sust.	Total $LS + s + HN$	Δl
1. Metals	0.015	-0.028	0.031	0.008
2. Non-met.	0.032	0.067	0.092	0.010
3. Chemical	0.013	-0.008	0.020	0.015
4. Machinery	0.023	-0.045	-0.013	-0.003
5. Electrical	0.038	-0.068	0.017	0.010
6. Transport	0.035	-0.045	0.004	0.004
7. Food	0.003	-0.001	0.001	0.003
8. Textile	0.005	-0.015	-0.003	-0.015
9. Furniture	0.009	-0.054	-0.037	0.013
10. Paper	0.001	0.021	0.023	-0.001

Concluding remarks

• There is biased technological change and is important. In the evidence presented for Spain labor-saving productivity induces output growth around 1.5% per year while Hicks-neutral about other 1.5%.

• Labor saving productivity has three effects on labor demand: displacement, compensation through output and substitution. The net balance of these effects can destroy jobs (in contrast to neutral productivity) but not necessarily does .

• The weak growth of Spanish manufacturing employment can however be hardly explained by total technical change (biased+neutral) in most of industries. The explanation should hence turn towards the evolution of (prices and) demand (δ).

• How demand, i.e. the δs of the firms evolve with market competition and product choices/innovation of the firms, is the grand absent of many discussions, but:

- Broad evidence that in Europe drive employment creation (and cycle).

- In our simple model they embody price competition by others (which reduces δ): some authors attribute to them manufacturing employment evolution in US.

- By contrast they explain much less in the growth of Chinese companies (except in a few sectors).

• At the end market growth and biased technological change may be also related because some products imply more biased technologies.

- It has been suggested endogenous choice of technology based on costs (Acemoglu, 2002).

- Possibly what we need today are models of endogenous choice of technology based on product or demand requirements of competition.