Universidade do Minho

Documentos de Trabalho

Working Paper Series

"Is Technology Factor-Neutral? Evidence from the US Manufacturing Sector"

Sushanta K. Mallick
Ricardo M. Sousa

NIPE WP 26/ 2012

NÚCLEO DE INVESTIGAÇÃO EM POLÍTICAS ECONÓMICAS

UNIVERSIDADE DO MINHO

"Is Technology Factor-Neutral? Evidence from the US Manufacturing Sector"

Sushanta K. Mallick
Ricardo M. Sousa

NIPE[*] WP 26/ 2012

URL:
http://www.eeg.uminho.pt/economia/nipe

Is Technology Factor-Neutral? Evidence from the US Manufacturing Sector

Sushanta K. Mallick[$] Ricardo M. Sousa[#]

[$] Queen Mary University of London, School of Business and Management, United Kingdom.

[#] University of Minho, Economic Policies Research Unit (NIPE) and Department of Economics, Portugal; London School of Economics, Financial Markets Group (FMG), United Kingdom.

ABSTRACT

This paper analyses the neutrality of technology using data from the NBER-CES Manufacturing industry database. We show that technology has a positive effect on the skilled-to-unskilled labour and wage ratios, offering a skill-premium for these skilled workers. We also find that technology has become more favourable towards skilled labour since the eighties, thereby, explaining the rise in the relative abundance of skilled workers. Finally, differences in productivity among the two labour inputs are important when they are relatively poor substitutes, despite the increase in the elasticity of substitution between unskilled and skilled labour that occurred over the past decades.

Keywords: Technological progress, skill premium, industry-level data.
JEL classification: O12, O47, D24, J24.

1. Introduction

Wage inequality between skilled and unskilled workers in the US has substantially increased since the early eighties (Kortum, 1993; OECD, 1993; Machin and van Reenen, 1998; Agnello and Sousa, 2012). Previous studies investigated the sources of US economic growth by decomposing changes in output into changes in factors of production and changes in overall total factor productivity and assuming that skilled and unskilled labour are perfect substitutes (Jones, 2005; Ha and Howitt, 2007).

In contrast, Greenwood and Yorukoglu (1997) argue that if skilled workers have a comparative advantage in technology implementation, the acceleration in investment-specific technology will increase productivity growth and wage inequality. Caselli (1999) shows that a biased technology revolution affects wage inequality if the workforce is heterogeneous in training cost. Acemoglu (2002) also finds that technology shifts favour skilled labour.

More recently, Caselli and Coleman (2006) study cross-country differences in skilled and unskilled labour efficiencies when skilled and unskilled labour are imperfect substitutes, and show that this characterization of the labour market provides a better understanding of the sources of the US growth. Additionally, the authors argue that the skill-biased nature of technology helps explaining the dramatic changes in the relative supply of skills, as well as the skill premium, that is, the ratio of the skilled labour wage to the unskilled labour wage.

In this paper, we look at the potential non-neutrality of technology using industry-level data from the NBER-CES Manufacturing database. Our empirical estimation is based on the disaggregated cross-section and time-series data from the US manufacturing sector. We find that total factor productivity raises both the ratio of skilled-to-unskilled labour and skilled-to-unskilled wage. Therefore, the empirical evidence suggests that technology is biased towards skilled labour.

We also show that the non-neutrality of technology became mostly relevant since the beginning of the eighties and contributed to explain the increase in the relative abundance of skilled labour.

Finally, we confirm that existence of a negative relationship between the degree of substitution between skilled and unskilled labour and total factor productivity. In particular, when the two labour inputs are poor substitutes, differences in productivity are extremely large and they have increased over the past decades. This, in turn, provides further evidence supporting the technology is factor-biased, despite the increase in the elasticity of substitution between unskilled and skilled labour.

The remainder of the paper is as follows. In Section 2, we provide a theoretical framework for non-neutrality of technology, which may affect the demand for skilled and unskilled workers. In Section 3, we put forward the empirically testable equations. In Section 4, we present the results using US manufacturing sector panel data. Section 5 concludes.

2. Theoretical Model

We follow Caselli and Coleman (2006) and consider a model with imperfect substitutability among skilled and unskilled labour and non-neutrality in technology. More specifically, we assume the following production function:

$$y = k^{\alpha}\left[(A_u L_u)^{\sigma} + (A_s L_s)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}}, \tag{1}$$

where y is the output per worker, k is the physical capital per worker, L_u is unskilled labour, L_s is skilled labour, and A_u and A_s the efficiency units embodied, respectively, in one unit of skilled labour and one unit of unskilled labour. The parameters α and σ are the ratio of capital per output and the elasticity of substitution between unskilled and skilled labour, respectively.

The two labour inputs are potentially imperfect substitutes (where $\sigma = 1$ corresponds to the perfect-substitutability case), because there is a constant elasticity of substitution (CES) aggregate of skilled and unskilled labour. Similarly, differences in technology are potentially non-neutral, as we allow there are factor-specific efficiency units, A_u and A_s (where $A_u = A_s = A$ denotes the case of factor-neutrality).

If the production factors are paid at their marginal productivity, the skill premium will be

$$\frac{w_s}{w_u} = \left(\frac{A_s}{A_u}\right)^{\sigma}\left(\frac{L_s}{L_u}\right)^{\sigma-1}. \tag{2}$$

Assuming that the aggregate technology itself, A, is a vector that includes two types of technology, A_u and A_s, then:

$$A = g(A_u, A_s) := \left(\frac{A_s}{A_u}\right). \tag{3}$$

Replacing (3) in (2), one gets:

$$\frac{w_s}{w_u} = A^{\sigma}\left(\frac{L_s}{L_u}\right)^{\sigma-1}. \tag{4}$$

In order to assess the (non-)neutrality of technology, we can consider four alternatives:

1. $L_s = L_u = \chi$, where χ is a constant, in which case we can rewrite equation (4) as:

$$\frac{w_s}{w_u} = A^{\sigma}\chi^{\sigma-1} := f(A). \tag{5}$$

2. $w_s = w_u = \chi$, where χ is a constant, in which case equation (4) can be expressed as

$$\frac{L_s}{L_u} = A^{\frac{\sigma}{1-\sigma}}\chi^{\frac{1}{\sigma-1}} := g(A). \tag{6}$$

3. $\frac{w_s}{w_u}$ and $\frac{L_s}{L_u}$ are unconstrained ratios and we calibrate the parameter σ to back out A, that is:

$$A = \left[\frac{w_s}{w_u}\left(\frac{L_s}{L_u}\right)^{1-\sigma}\right]^{1/\sigma}. \tag{7}$$

4. $\frac{w_s}{w_u}$ and $\frac{L_s}{L_u}$ are unconstrained ratios and we use data on A to back out the parameter σ, that is:

$$\sigma = \frac{\ln\left(\frac{w_s}{w_u}\cdot\frac{L_s}{L_u}\right)}{\ln\left(A\cdot\frac{L_s}{L_u}\right)}. \tag{8}$$

3. Econometric Methodology

We estimate the econometric counterparts of theoretical models (5) and (6) for a panel of N industries (indexed by i = 1, ..., N) over T years (indexed by t = 1, ..., T), respectively, as:

$$\left(\frac{w_s}{w_u}\right)_{i,t} = \alpha + \beta A_{i,t} + \varepsilon_{i,t}, \tag{9}$$

$$\left(\frac{L_s}{L_u}\right)_{i,t} = \alpha + \beta A_{i,t} + \varepsilon_{i,t}. \tag{10}$$

In doing so, we use different econometric methodologies, namely: (i) fixed-effects; (ii) fixed effects with time effects; (iii) random effects; and (iv) random effects with time effects.

In addition, we use equation (7) to back out the technology parameter, A, by calibrating the parameter σ for different values. Autor et al. (1998) suggest that the elasticity of substitution, σ, should range between 1 and 2 and Katz and Murphy (1992) set $1/(1 - \sigma)$ equal to 1.4.

Finally, after backing out the parameter σ in equation (8), we assess its importance at explaining the variation in the wage ratio, $\frac{w_s}{w_u}$, over time.

4. Data and Empirical Results

We use data from the NBER-CES Manufacturing Industry Database. This database is a joint effort between the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies. Industry total factor productivity (TFP) and employment data are taken from the NBER Manufacturing Productivity Database (Becker and Gray, 2009) to estimate the relationship between skill premium and TFP. It contains annual industry-level data on capital stock, employment, investment, output, payroll and other input costs, total factor productivity (TFP) and various industry-specific price indexes. It covers all 4-digit SIC (and 6-digit NAICS) manufacturing industries from 1958-2005, in two versions -1987 SIC codes (459 industries) and 1997 NAICS codes (473 industries) - and they largely reflect information in the Annual Surveys of Manufacturing.

Data on total employment, L, and production (or unskilled) workers, L_u, is used to back out non-production (or skilled) workers, L_s. Similarly, data on total payroll, w, and production worker wages, w_u, is used to compute non-production worker wages, w_s. Data on productivity, A, corresponds to TFP.[1]

Table 1 summarizes the impact of technology on the skilled-to-unskilled labour ratio (Panel A) and the skilled-to-unskilled wage ratio (Panel B) over the period 1958-2005. It can be seen that all econometric methodologies suggest that an increase in total

[1] Although TFP measurement may be questionable, Becker and Gray (2009) have done an excellent job in deriving multi-factor TFP, which can be used as a measure of technological change as contained in the database and is based on measuring separate factor of inputs for non-energy materials, energy, labour, and capital. For more details, see also Carlaw and Lipsey (2003) and Krüger (2003).

factor productivity has a positive effect on both ratios, thereby highlighting that technological progress is biased towards skilled labour. In particular, technological progress explains: (i) between 1.8% and 17.1% of the variation in the labour ratio; and (ii) 1.4% to 20.9% of the change in the wage ratio.

[Table 1 about here]

Tables 2 and 3 provide the sub-sample analysis for periods 1958-1979 and 1980-2005, respectively. Interestingly, the evidence points to positive effects of technology on the labour ratio in both sub-samples. Moreover, the coefficient estimates associated to technology in the labour ratio regressions are larger in magnitude for the second period than for the first period. This piece of evidence suggests that, in the eighties, the neutrality of technology has shifted towards a framework that is more favourable in terms of quantities (the labour ratio) of skilled labour. Putting it differently, the non-neutrality of technology has pushed for a more intensive use of skilled labour, a feature that confirms the observation that new technologies introduced in the eighties have generally led to a replacement of unskilled labour and required skilled labour (Sill, 2002).

In what concerns the wage ratio, the results support the existence of a positive impact of technology, but only in the first sub-sample period. This result is consistent with the work of Mitchell (2005), who argues that, even with an increasing demand for skilled labour over time, specialization is deskilling. In the same line, Kaboshi (2005) shows that the trend in skill premium can be motivated by changes in the willingness to acquire schooling. This, in turn, depends on schooling costs, which have largely risen due to a lower share of government funding for education (in percentage of GDP).

[Table 2 about here]

[Table 3 about here]

In Table 4, we present the implied technology associated with a range of values for the elasticity of substitution between skilled and unskilled labour, σ. The findings clearly corroborate the idea that technology is non-neutral. In fact, implied values for A depart substantially from 1 (the case of neutrality) and are typically large, i.e. productivity of skilled labour exceeds productivity of unskilled labour. For instance, when $1/(1-\sigma)$ is equal to 1.4, the implied value for A is above 100, which confirms that differences in productivity among the two labour types are relevant. Finally, there is a negative relationship between σ and the implied value for A. Putting it differently, when σ is low, the two inputs are poor substitutes and firms operate with positive quantities of both types of labour. However, as σ becomes larger (i.e. L_s and L_u become better substitutes), firms start reducing the quantity of one of the two inputs. Consequently, when inputs are good substitutes, industries that are abundant in unskilled labour will choose unskilled labour-augmenting technologies; when inputs are poor substitutes, industries with abundant unskilled labour will boost productivity by increasing the quantity used of skilled labour.

[Table 4 about here]

Tables 5 and 6 provide a summary of the implied technology associated with a range of values for the elasticity of substitution between skilled and unskilled labour, σ, for the two sub-sample periods considered before, i.e. 1958-1979 and 1980-2005. The results again support the negative link between σ and A. In addition, they confirm the importance of the non-neutrality of technology and suggest that this has become stronger in the second period. Indeed, when $1/(1-\sigma)$ is equal to 1.4, the implied value for A is 77.83 over the period 1958-1979 and 124.27 in 1980-2005.

[Table 5 about here]

[Table 6 about here]

Finally, in Table 7, we report the implied value for σ, which is obtained by using the data on $\frac{w_s}{w_u}$, $\frac{L_s}{L_u}$ and A. For the full sample, implied value for the elasticity of substitution between unskilled and skilled labour, 1.56, is in line with the one found in previous studies, 1.4. However, it can be seen that the degree of substitution between the two types of labour has increased: the implied value for σ was 1.47 in 1958-1979 and 1.64 in 1980-2005. This helps explaining why the responsiveness of the wage ratio to changes in the labour ratio has declined or, equivalently, why the relationship between $\frac{L_s}{L_u}$ and $\frac{w_s}{w_u}$ has become flatter.

[Table 7 about here]

5. Conclusion

This paper assesses the potential non-neutrality of technology using data from the NBER-CES Manufacturing industry database. We find that technology has a positive and significant impact on both the ratio of skilled-to-unskilled labour and the skilled-to-unskilled wage ratio. We also show that technology has become biased towards skilled labour and has contributed for a rise in the labour ratio since the beginning of the eighties. Finally, we confirm that when the two labour inputs are poor substitutes, differences in productivity are substantial. However, the elasticity of substitution between unskilled and skilled labour has increased over the past decades.

References

Acemoglu, D., 2002. Technical change, inequality, and the labor market. Journal of Economic Literature, 40(1), 7-72.

Agnello, L., and R. M. Sousa, 2012. Fiscal adjustments and income inequality: A first assessment. Applied Economics Letters, 19(16), 1627-1632.

Autor, D. H., Katz, L. F., and A. B. Krueger, 1998. Computing inequality: Have computers changed the labour market? The Quarterly Journal of Economics, 113(4), 1169-1213.

Becker, R. A., and W. B. Gray, 2009. NBER-CES Manufacturing Industry Database, May, at http://www.nber.org/data/nbprod2005.html.

Carlaw, K. I. and R. G. Lipsey, 2003. Productivity, technology and economic growth: What is the relationship? Journal of Economic Surveys, 17, 457-495.

Caselli, F., 1999. Technological revolutions. American Economic Review, 89, 78-102.

Caselli, F., and W. J. Coleman, 2006. The world technology frontier. American Economic Review, 96(3), 499-522.

Greenwood, J., and M. Yorukoglu, 1997. Carnegie-Rochester Conference Series on Public Policy, 46, 49-95.

Ha, J., and P. Howitt, 2007. Accounting for trends in productivity and R&D: A Schumpeterian critique of semi-endogenous growth theory. Journal of Money, Credit, and Banking, 33, 733-774.

Jones, C. I., 2005. The shape of production functions and the direction of technical change. Quarterly Journal of Economics, 120(2), 517-549.

Kaboshi, J. P., 2005. Supply factors and the mid-century fall in the skill premium. Ohio State University, Working Paper.

Katz, L. F., and K. M. Murphy, 1992. Changes in relative wages, 1963-1987: Supply and demand factors. Quarterly Journal of Economics, 1, 35-78.

Kortum, S., 1993. Equilibrium R&D and the patent-R&D ratio: U.S. evidence. American Economic Review, 83, 450-457.

Krüger, J. J., 2003. The global trends of total factor productivity: evidence from the nonparametric Malmquist index approach. Oxford Economic Papers, April, 55(2), 265-286.

Machin, S., and J. van Reenen, 1998. Technology and changes in skill structure: Evidence from seven OECD countries. Quarterly Journal of Economics, 113, 1215-1244.

Mitchell, M. F., 2005. Specialization and the skill premium in the 20th Century. International Economic Review, 46(3), 935-955.

OECD, 1993. Employment Outlook. OECD: Paris.Sill, K., 2002. Widening the wage gap: The skill premium and technology. Federal Reserve Bank of Philadelphia Business Review, Q4, 25-32.

Sill, K., 2002. Widening the wage gap: The skill premium and technology. Federal Reserve Bank of Philadelphia Business Review, Q4, 25-32.

List of Tables

Table 1: Impact of technology on labour and wage ratio (full sample).

	Panel A: L_s/L_u			
	FE	FE	RE	RE
A	0.0311***	0.0229***	0.0312***	0.0229***
	[19.97]	[15.84]	[20.00]	[15.84]
Time effects		Yes		Yes
Observations	21955	21955	21955	21955
Adjusted-R2	0.0182	0.1714	0.0182	0.1714
	Panel B: w_s/w_u			
	FE	FE	RE	RE
	0.0473***	0.0298***	0.0474***	0.0299***
	[17.43]	[12.15]	[17.47]	[12.18]
Time effects		Yes		Yes
Observations	21955	21955	21955	21955
Adjusted-R2	0.0139	0.2089	0.0139	0.2089

Note: *t*-statistics in square brackets. ***, **, * - statistically significant at 1%, 5% and 10% level, respectively.

Table 2: Impact of technology on labour and wage ratio (first sub-sample: 1958-1979).

	Panel A: L_s/L_u			
	FE	FE	RE	RE
A	0.0313***	0.0027	0.0299***	0.0016
	[4.30]	[0.36]	[4.13]	[0.22]
Time effects		Yes		Yes
Observations	10098	10098	10098	10098
Adjusted-R2	0.0019	0.0634	0.0019	0.0634
	Panel B: w_s/w_u			
	FE	FE	RE	RE
	0.0656***	0.0100	0.0617***	0.0068
	[5.78]	[0.86]	[5.48]	[0.59]
Time effects		Yes		Yes
Observations	10098	10098	10098	10098
Adjusted-R2	0.0035	0.0722	0.0035	0.0722

Note: *t*-statistics in square brackets. ***, **, * - statistically significant at 1%, 5% and 10% level, respectively.

Table 3: Impact of technology on labour and wage ratio (second sub-sample: 1980-2005).

	Panel A: L_s/L_u			
	FE	FE	RE	RE
A	0.0066***	0.0049***	0.0068***	0.0051***
	[4.60]	[2.71]	[4.70]	[3.59]
Time effects		Yes		Yes
Observations	11857	11857	11857	11857
Adjusted-R2	0.0019	0.0501	0.0019	0.0501
	Panel B: w_s/w_u			
	FE	FE	RE	RE
	-0.0029	-0.0085***	-0.0025	-0.0080***
	[-1.15]	[-3.55]	[-1.00]	[-3.35]
Time effects		Yes		Yes
Observations	11857	11857	11857	11857
Adjusted-R2	0.0001	0.1024	0.0001	0.1024

Note: *t*-statistics in square brackets. ***, **, * - statistically significant at 1%, 5% and 10% level, respectively.

Table 4: Implied technology for a range of σ.

1/(1-σ)	Implied A
1.1	1.74×10^{14}
1.2	9.11×10^{5}
1.3	2.01×10^{3}
1.4	1.03×10^{2}
1.5	18.87
1.6	6.31
1.7	3.06
1.8	1.89
1.9	1.32
2.0	1.04

Table 5: Implied technology for a range of σ (first sub-sample: 1958-1979).

1/(1-σ)	Implied A
1.1	3.62×10^{13}
1.2	4.64×10^{5}
1.3	1.36×10^{3}
1.4	77.83
1.5	14.87
1.6	5.00
1.7	2.39
1.8	1.45
1.9	1.00
2.0	0.78

Table 6: Implied technology for a range of σ (second sub-sample: 1980-2005).

$1/(1-\sigma)$	Implied A
1.1	2.91×10^{14}
1.2	1.29×10^{6}
1.3	2.57×10^{3}
1.4	1.24×10^{2}
1.5	22.28
1.6	7.42
1.7	3.62
1.8	2.25
1.9	1.60
2.0	1.27

Table 7: Implied σ.

σ
Panel A: Full sample
1.56
Panel B: 1958-1979
1.47
Panel C: 1980-2005
1.64

Most Recent Working Paper

NIPE WP 26/2012	Sushanta K. Mallick e **Ricardo M. Sousa**, “Is Technology Factor-Neutral? Evidence from the US Manufacturing Sector” 2012
NIPE WP 25/2012	Jawadi, F. e **Ricardo M. Sousa**, “Structural Breaks and Nonlinearity in US and UK Public Debt” 2012
NIPE WP 24/2012	Jawadi, F. e **Ricardo M. Sousa**, “Consumption and Wealth in the US, the UK and the Euro Area: A Nonlinear Investigation” 2012
NIPE WP 23/2012	Jawadi, F. e **Ricardo M. Sousa**, “ Modelling Money Demand: Further Evidence from an International Comparison” 2012
NIPE WP 22/2012	Jawadi, F. e **Ricardo M. Sousa**, “ Money Demand in the euro area, the US and the UK: Assessing the Role of Nonlinearity” 2012
NIPE WP 21/2012	Agnello, L, Sushanta K. Mallick e **Ricardo M. Sousa**, “Financial Reforms and Income Inequality” 2012
NIPE WP 20/2012	Agnello, L, Gilles Dufrénot e **Ricardo M. Sousa**, “Adjusting the U.S. Fiscal Policy for Asset Prices: Evidence from a TVP-MS Framework t” 2012
NIPE WP 19/2012	Agnello, L e **Ricardo M. Sousa**, “Fiscal Adjustments and Income Inequality: A First Assessment” 2012
NIPE WP 18/2012	Agnello, L, **Vitor Castro** e **Ricardo M. Sousa**, “Are there change-points in the likelihood of a fiscal consolidation ending?” 2012
NIPE WP 17/2012	Agnello, L, **Vitor Castro** e **Ricardo M. Sousa**, “What determines the duration of a fiscal consolidation program?” 2012
NIPE WP 16/2012	**Veiga, Linda,** “Voting functions in the EU-15”, 2012
NIPE WP 15/2012	**Alexandre, Fernando** e Pedro Bação, “Portugal before and after the European Union: Facts on Nontradables”, 2012
NIPE WP 14/2012	**Esteves, Rosa Branca** e Carlo Reggiani, “Behaviour-Based Price Discrimination with Elastic Demand”, 2012
NIPE WP 13/2012	**Afonso, Oscar, Sara Monteiro, Maria Thompson** “ Innovation Economy, Productive Public Expenditures and Economic Growth ”, 2012
NIPE WP 12/2012	**Esteves, Rosa Branca** “ Price Discrimination with Private and Imperfect Information”, 2012
NIPE WP 11/2012	**Castro, Vítor** “Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI”, 2012
NIPE WP 10/2012	Bastos, Paulo, **Natália Pimenta Monteiro e Odd Rune Straume** “Privatization and corporate restructuring”, 2012
NIPE WP 09/2012	**Castro, Vítor** e Rodrigo Martins “Is there duration dependence in Portuguese local governments’ tenure?”, 2012
NIPE WP 08/2012	**Monteiro, Natália Pimenta** e Geoff Stewart “ Scale, Scope and Survival: A Comparison of Labour-Managed, and Capitalist Modes of Production”, 2012
NIPE WP 07/2012	**Aguiar - Conraria, Luís,** Teresa Maria Rodrigues **e Maria Joana Soares** “ Oil Shocks and the Euro as an Optimum Currency Area”, 2012
NIPE WP 06/2012	Bastos, Paulo,**Odd Rune Straume** e Jaime A. Urrego “Rain, Food and Tariffs ”, 2012
NIPE WP 05/2012	Brekke, Kurt R., Luigi Siciliani e **Odd Rune Straume,** “Can competition reduce quality?”, 2012
NIPE WP 04/2012	Brekke, Kurt R., Luigi Siciliani e **Odd Rune Straume,** “Hospital competition with soft budgets”, 2012
NIPE WP 03/2012	Lommerud, Kjell Erik, **Odd Rune Straume** e Steinar Vagstad**,** “ Employment protection and unemployment benefits: On technology adoption and job creation in a matching model”, 2012
NIPE WP 02/2012	**Amado, Cristina** e Timo Teräsvirta, “Modelling Changes in the Unconditional Variance of Long Stock Return Series”, 2012
NIPE WP 01/2012	Martins, Rodrigo e **Francisco José Veiga**, “ Turnout and the modeling of economic conditions: Evidence from Portuguese elections”, 2012