MORE JOBS BUT LESS PRODUCTIVE?
THE IMPACT OF LABOUR MARKET POLICIES ON PRODUCTIVITY

FURTHER MATERIAL

This document contains additional annexes to Chapter 2, "More Jobs But Less Productive: The Impact of Labour Market Policies on Productivity", of the 2007 edition of the ***OECD Employment Outlook***. The complete versions of Employment Outlook are available online, on free access, one year after their publication on: www.oecd.org/els/employmentoutlook.

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ANNEX 2.A2

IMPACT OF TRAINING ON PRODUCTIVITY

The elasticity of multi-factor productivity (MFP) to the stock of human capital accumulated through workplace training, reported in Box 2.1 of OECD (2007) is estimated by fitting the following augmented production function:

$$\log y_{ijt} = \delta \log k_{ijt} + \beta \log T_{ijt} + \mu_{ij} + \chi_{it} + \varepsilon_{ijt} \qquad [1]$$

where y is labour productivity, k is the capital-labour ratio, T is the training stock per worker, i, j, and t index country, industry and time respectively, and Greek letters represent coefficients or disturbances. This specification departs from existing industry-level estimates where training stocks are computed on the basis of training participation rates (Barrett and O'Connell, 2001; Dearden, Reed and van Reenen, 2005; Conti, 2005), insofar as training stocks are specified in logarithms rather than in absolute levels. Yet, specifications including level training stocks are justified in the literature under the unrealistic assumption that workers can be divided into two homogeneous groups (trained and untrained). By contrast, if human capital is thought to be a continuous variable, with training participation rates indicating the frequency of human capital investments, a logarithmic specification appears to be more reasonable (see *e.g.* Ballot, Fakhfakh and Taymaz, 2001, 2006, who use training stocks computed from continuous measures of training investment).

Equations are estimated using OLS and system GMM, where training and capital stocks are treated as endogenous variables. The results shown in Table 2.A2.1 are from OLS specifications where fixed effects are included to capture two-dimensional disturbances.

Table 2.A2.1. **Impact of employee training on MFP[a] – OLS estimates**

	Total business industries		Manufacturing and utilities		Construction and services	
Training	0.036	[2.49]**	0.036	[2.36]**	0.033	[1.03]
Capital stock	0.255	[6.99]***	0.252	[5.95]***	0.268	[4.59]***
Country x year dummies	yes		yes		yes	
Country x year x service industry dummies	yes		yes		yes	
Country x industry dummies	yes		yes		yes	
Industry x year dummies	yes		no		yes	
Observations	1585		1065		520	
R-squared	1		1		1	

MFP: Multi-factor productivity; OLS: Ordinary least squares.
Robust t-statistics in brackets. ** significant at 5%; *** significant at 1%.
a) Dependent variable is the logarithm of labour productivity. Training is the logarithm of training stock per worker. Capital stock is the logarithm of the capital-to-labour ratio. For each country *i* and year *t*, the corresponding country-by-year-by-service industry dummies take value 1 in construction and services and 0 elsewhere. See OECD (2007), Annex 2.A1 for details on data and sources.

Source: OECD estimates.

The results shown in Table 2.A2.2 are estimated using System GMM estimators, which use (appropriately) lagged levels of endogenous explanatory variables as instruments for their current variation as well as lagged differences as instruments for their current levels (see *e.g.* Blundell and Bond, 1998). In specifications estimated by GMM, each variable is demeaned by subtracting its country-by-time mean in order to control for country-by-time effects without incurring the risk of having a number of instruments greater than the number of panels.

Table 2.A2.2. **Impact of employee training on MFP[a] – GMM estimates[b]**

	Total business industries		Manufacturing and utilities	
Training	0.144	[1.72]*	0.130	[1.76]*
Capital stock	0.229	[2.16]**	0.262	[2.89]***
Country x year dummies	yes		yes	
Country x year x service sector dummies	yes		yes	
Country x sector dummies	no		no	
Sector x year dummies	no		no	
Sector dummies	yes		yes	
Hansen-Sargan test (P-value)	0.312		0.307	
Arellano-Bond AR1 test	-3.5		-3.45	
Arellano-Bond AR2 test	-0.22		-0.49	
Observations	1055		685	

MFP: Multi-factor productivity; GMM: One-step system generalised method of moments.
Robust t-statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.
a) Dependent variable is the logarithm of labour productivity. Training is the logarithm of training stock per worker. Capital stock is the logarithm of the capital-to-labour ratio. See OECD (2007), Annex 2.A1 for details on data and sources.
b) The error term in the GMM specification is modelled as an ARMA process with up to an AR(2) component (choice made on diagnostics). Productivity, capital stock and training are treated as endogenous variables. The common factor restriction is not imposed. Only long-run effects are presented. In order to control for country-by-time-by-manufacturing/service effects, each variable is demeaned by subtracting its country-by-time-by-manufacturing/service mean. Productivity capital stock and training dated *t-a*-1 to *t-a*-3 (where *a* is sum of the orders of the AR and MA components) are used as instruments in the difference equation. The Hansen-Sargan statistic provides a test of overidentifying restrictions. The model is rejected if the statistic is significant. Arellano-Bond statistics test the autocorrelation of the first difference of the residuals at order 1 and 2 and are normally distributed under the null. The model is rejected if evidence of autocorrelation is found at order 2.

Source: OECD estimates.

Augmented production functions such as [1] are estimated using comparable cross-country data on training and productivity for European countries. Training stock data are reconstructed from training participation rates from the 1992 to 2002 waves of the European Labour Force Survey for Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden and the United Kingdom. These were matched with data from the OECD STAN Database and the Groningen Growth and Development Centre 60-Industry Database on productivity and capital stock at the industry-level. Due to data availability, not all years or industries are included in the estimation sample (see OECD, 2007, Annex 2.A1 for more details on data and sources). In the case of GMM, due to the demeaning procedure (see above), for each country the sample is reduced to the same number of industry in each year. For this reason, the sample size is too small to estimate [1] on construction and service industries only.

References

Ballot, G., F. Fakhfakh and E. Taymaz (2001), “Firms’ Human Capital, R&D and Performance: A Study on French and Swedish Firms”, *Labour Economics*, vol. 8, no. 4, pp. 443-462.

Ballot, G., F. Fakhfakh and E. Taymaz (2006), “Who Benefits from Training and R&D, the Firm or the Workers?”, *British Journal of Industrial Relations*, vol. 44, no. 3, pp. 473-495.

Barrett, A. and P.J. O’Connell (2001), “Does Training Generally Work? The Returns to In-Company Training”, *Industrial and Labor Relations Review*, vol. 54, no. 3, pp. 647-662.

Blundell, R. and S. Bond (1998), “Initial Conditions and Moment Restrictions in Dynamic Panel Data Models”, *Journal of Econometrics*, vol. 87, no. 1, pp. 115-143.

Dearden, L., H. Reed and J. van Reenen (2006), “The Impact of Training on Productivity and Wages: Evidence from British Panel Data”, *Oxford Bulletin of Economic and Statistics*, vol. 68, no. 4, pp. 397-421.

OECD (2007), *OECD Employment Outlook*, OECD, Paris.

ANNEX 2.A3

COMPOSITION EFFECTS IN AGGREGATE AND INDUSTRY-LEVEL ANALYSES

Aggregate relationship between labour utilisation and labour productivity

As discussed in Section 1.2 of OECD (2007), increases in the employment rate or hours worked are likely to reduce average measured labour productivity for three reasons. First, because skilled workers are more likely to be employed than unskilled workers, an increase in the employment rate is likely to increase the proportion of unskilled workers in the workforce. This will reduce the average quality of labour input and reduce measured productivity, which does not control for labour quality. Second, productivity will be reduced due to diminishing returns to labour input (particularly in the case of an increase in hours worked with no change in the employment rate). Third, if employment and hours increase because of a labour supply surge, labour intensive industries (with lower labour and possibly multi-factor productivity) are likely to expand.

The relationship between labour productivity growth and the growth of total hours per capita can be estimated in levels, controlling for fixed country factors as well as shocks that are common across countries, that is:

$$\log y_{it} = \delta \log l_{it} + \eta_i + \lambda_t + \varepsilon_{it} \qquad [2]$$

where $y = Y/L$ is labour productivity, l is total hours per capita, i and t index country and time, respectively, η and λ represent country and time effects, respectively, χ represents the disturbance and δ the parameter to be estimated. It might be tempting to interpret OLS estimates of δ as estimates of the elasticity of labour productivity growth to employment growth (that is as a measure of the possible "composition effect" of policies affecting employment on productivity). Yet, this conclusion would be unwarranted insofar as policies and other factors can have an independent impact on productivity, which is not due to their impact on labour utilisation. However, it is difficult, in an aggregate context, to find a suitable instrument that affects employment without directly affecting productivity. Nonetheless, one can interpret OLS estimates as providing an upper bound (in absolute value) to the true composition effect.

The aggregate impact of employment on productivity is estimated by OLS on annual data for the years 1970-2003 for 21 OECD countries. The countries included in the sample are Australia, Austria (1995-2003), Belgium, Canada, Denmark, Finland, France, Germany (1993-2003), Greece (1983-2003), Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Portugal (1986-2003), Spain, Sweden, Switzerland (1975-2003), the United Kingdom and the United States. Column 1 of Table 2.A3.1 shows a very strong negative relationship between labour productivity and total hours per capita over the past three decades. Removing Australia, New Zealand and Switzerland and limiting the time period used in the estimation to that following the second oil price shock of the 1970s (to make the estimates comparable with the industry-level results presented in the next section) gives a weaker, but still sizeable and statistically significant, relationship (column 2).

These correlations suggest that composition effects, in the absence of valid instruments, cannot be easily dismissed in an aggregate analysis. By the same token this implies that an aggregate analysis of the impact of policies on productivity will be unable to estimate any other independent effect of policies on productivity. The resulting findings will therefore be of little practical use for policy guidance.

Table 2.A3.1. **Aggregate estimates of relationship between total hours per capita and labour productivity**

Aggregate estimates using OLS

	All countries		All countries excluding Australia, NZ & Switzerland & years prior to 1979	
Total hours per capita	-0.857	[17.29]***	-0.435	[6.27]***
Country dummies	yes		yes	
Year dummies	yes		yes	
Observations	628		405	
R-squared	1		1	

OLS: ordinary least squares.
Robust t-statistics in brackets. *** significant at 1%.
Data for labour productivity (GDP in volume terms divided by total hours worked) and total hours per capita (employment rate of the population aged 15 to 64 years multiplied by average hours per person employed) are from the OECD Productivity Database.

Source: OECD estimates.

Industry-level relationship between labour utilisation and labour productivity

Using industry-level data it is possible to look at the within-industry relationship between labour utilisation and productivity while controlling for aggregate effects using time-by-country dummies. This implies estimating a specification of the following type:

$$\log y_{ijt} = \delta \log l_{ijt} + \mu_{ij} + \chi_{it} + \varepsilon_{ijt} \qquad [3]$$

where y is labour productivity, l is total hours per capita, i, j, and t index country, industry and time respectively, and Greek letters represent coefficients or disturbances.

This relationship is estimated using the same sample of countries and years as the results presented in column 2 of Table 2.A3.1. The sample includes industry-level data for all industries except agriculture, hunting, forestry and fishing, mining and quarrying, business services, public administration and defence, education, health and social work and other community, social and personal services. Data sources are outlined in Annex 2.A1 of OECD (2007).

Columns 1 and 2 of Table 2.A3.2 show the results from an OLS estimation of [3], including fixed effects for any two-dimensional disturbance. While the negative association between labour utilisation and labour productivity is still negative and statistically significant, the estimated coefficient is much smaller than the aggregate estimates in Table 2.A3.1. This coefficient is further reduced by about one half if the capital/labour ratio is included in the list of controls (results not shown in Table 2.A3.2).

Table 2.A3.2. **Industry level estimates of relationship between total hours per capita and labour productivity**

Industry-level estimates using OLS and GMM models

	OLS				GMM			
	Total business sector		Manufacturing & utilities		Total business sector		Manufacturing & utilities	
Total hours per capita	-0.143	[9.92]***	-0.042	[2.00]**	0.034	[0.97]	0.050	[1.22]
Sector dummies	yes		yes		yes		yes	
Country x year dummies	yes		yes		yes		yes	
Country x sector dummies	yes		yes		no		no	
Hansen-Sargan test (P-value)					0.166		0.484	
Arellano-Bond AR1 test					-9.44	***	-6.32	***
Arellano-Bond AR2 test					-1.96	*	1.28	
Observations	6880		4730		6560		4290	
R-squared	1		1					

OLS: Ordinary least squares; GMM: One-step system generalised method of moments.
In GMM models, the error term is modelled as an ARMA process with up to an AR(2) component (choice made on diagnostics). Productivity and hours per capita are treated as endogenous variables. The common factor restriction is not imposed. Only long-run effects are presented. In order to control for country by time effects (country x year dummies), each variable is demeaned by subtracting its country by time means. Productivity and hours dated *t-a*-1 to *t-a*-3 (where *a* is sum of the orders of the AR and MA components) are used as instruments in the difference equation. The Hansen-Sargan statistic provides a test of overidentifying restrictions. The model is rejected if the statistic is significant. Arellano-Bond statistics test the autocorrelation of the first difference of the residuals at order 1 and 2 and are normally distributed under the null. The model is rejected if evidence of autocorrelation is found at order 2.
Robust t-statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: OECD estimates.

It might be difficult however to interpret these estimates as an upper bound to within-industry composition effects. If workers tend to flow to industries where productivity (and wages) are higher, OLS estimates could also be upward-biased and the real within-industry elasticity greater (in absolute value) instead of smaller or zero. However, with industry-level data, there is a sufficiently large panel to use an instrumental variables approach to control for endogeneity by exploiting the time-series properties of the data. Equation [3] is re-estimated using System GMM estimators with (appropriately) lagged levels of endogenous explanatory variables as instruments for their current variation as well as lagged differences as instruments for their current levels (see *e.g.* Blundell and Bond, 1998). The results are reported in columns 3 and 4 of Table 2.A3.2. No evidence emerges to suggest that the OLS estimates are upward biased.

Overall, the results presented in Table 2.A3.2 suggest that within-industry composition effects are negligible, and industry-level analyses, where feasible, can meaningfully shed light on the independent impact of selected labour market policies on productivity.

Reference

OECD (2007), *OECD Employment Outlook*, OECD, Paris.

ANNEX 2.A4

IMPACT OF UNEMPLOYMENT BENEFITS ON GDP PER CAPITA GROWTH

Table 2.A4.1 presents the results of pooled mean group (PMG) estimates of the impact of unemployment benefits (as measured by an average of gross replacement rates across various earnings levels, family situations and durations of employment) on growth of GDP per capita. A description of the estimation method can be found in Box 2.2 of OECD (2007).

Table 2.A4.1. **Effect of unemployment benefits on GDP per capita**[a]

Results from PMG estimation of GDP per capita growth convergence models

	Baseline		Baseline + PMR		Baseline + Initial unemployment benefit replacement rate + unemployment benefit duration	
Convergence coefficient	-0.114	(5.57)***	-0.190	(3.38)***	-0.214	(8.32)***
Investment rate	0.171	(2.28)**	0.225	(6.81)***	0.360	(8.82)***
Human capital	0.755	(2.09)**	1.280	(5.73)***	0.792	(5.91)***
Population growth	-10.998	(3.88)***	-3.648	(4.24)***	-6.740	(5.35)***
Average replacement rate	-0.001	(0.37)	-0.001	(0.47)		
Initial unemployment benefit replacement rate (%)					0.001	(0.56)
Unemployment benefit duration (years)					-0.180	(0.99)
PMR			-0.101	(8.39)***		
Tax revenue to GDP ratio	-0.513	(3.01)***	-0.470	(7.57)***	-0.269	(3.32)***
Country dummies	yes		yes		yes	
Country x period [b] dummies	yes		yes		yes	
Observations	576		576		540	

	Baseline + PMR + Initial unemployment benefit replacement rate + unemployment benefit duration		Baseline + Initial unemployment benefit replacement rate		Baseline + PMR + Initial unemployment benefit replacement rate	
Convergence coefficient	-0.248	(7.92)***	-0.221	(8.20)***	-0.258	(7.81)***
Investment rate	0.356	(9.95)***	0.372	(9.04)***	0.352	(10.19)***
Human capital	0.520	(3.28)***	0.825	(8.27)***	0.593	(5.00)***
Population growth	-5.566	(4.68)***	-6.749	(5.74)***	-6.194	(5.76)***
Average replacement rate						
Initial unemployment benefit replacement rate (%)	0.002	(1.98)**	0.000	(0.19)	0.001	(1.13)
Unemployment benefit duration (years)	-0.081	(0.36)				
PMR	-0.038	(4.42)***			-0.035	(4.27)***
Tax revenue to GDP ratio	-0.282	(4.02)***	-0.238	(3.10)***	-0.226	(3.40)***
Country dummies	yes		yes		yes	
Country x period [b] dummies	yes		yes		yes	
Observations	540		540		540	

PMG: Pooled Mean Group; PMR: Product market regulation.
Absolute value of z-statistics in brackets. ** significant at 5%; *** significant at 1%.
a) Dependent variable is the first-difference of the logarithm of GDP per capita. Investment rate and human capital are expressed in logarithms. All specifications include first-differenced terms for all variables. Only the average of the convergence coefficients and long-run coefficients are reported. For explanation of other variables, see OECD (2007), Annex 2.A1.
b) Period is 5 years.

Source: OECD estimates.

Reference

OECD (2007), *OECD Employment Outlook*, OECD, Paris.