Barriers to Entry, Deregulation and Workplace Training^{*}

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Preliminary draft

Abstract

We develop a theoretical and empirical analysis of the impact of barriers to entry on workplace training. Our theoretical model indicates that there are two contrasting effects of deregulation on training. On the one hand, as stressed in the literature, with a given number of firms profits per unit of output fall, reducing the size of rents firms can enjoy if they train their employees. On the other hand, the number of firms increases following deregulation, thereby raising the output gain from training and improving investment incentives. While the balance of these effects is uncertain, numerical simulations show that for reasonable values of the parameters a positive relationship between deregulation and training prevails. We use repeated cross section data from the European Labour Force Survey to investigate empirically the relationship between product market regulation and training incidence in a sample of 15 European countries and 12 industrial sectors, which we follow for about 8 years. Our empirical results are unambiguous and show that a 10 percent increase in product market deregulation increases training incidence in the exposed industries by 2.8 to 5 percent, depending on the selected empirical specification.

Key words: training, product market competition, Europe

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Introduction

Product and labour market deregulation have attracted considerable attention by economists and policy makers, and there is a broad concern that these regulations can hamper growth and increase unemployment (see Blanchard and Giavazzi, 2003, Alesina et al, 2005). Empirical research on the economic effects of product market regulation and deregulation has focused so far on employment (Kugler and Pica, 2004), productivity growth (Nicoletti and Scarpetta, 2003, Aghion et al. 2006), investment in capital stock (Alesina et al, 2005), innovation (Aghion et al., 2005), and easiness to start a business (Djankov et al, 2001).

This paper develops a theoretical and empirical analysis of the relationship between product market regulation / deregulation and workplace training, which we define as the accumulation of human capital taking place while in employment and after school completion. We believe that looking at training is important because the production of skills is perceived as one of the main factors affecting productivity growth (see e.g. OECD, 2007). A casual look at available industry-level cross-country data reveals that the degree of stringency of product market regulation and the training participation rate are negatively correlated. Using data from the European Labour Force Survey and the OECD regulatory database which cover the years 1995-2002, Figure 1 illustrates this for 15 European countries and 3 non-manufacturing sectors (energy, transports and communication).¹ It turns out that the regulation index accounts for about 50 percent of the total variance of training. Yet, the prevailing view in the labour economics literature is that product market competition depresses training because it compresses the size of the rents that can be appropriated by firms which invest in human capital and pay for most of job-related training (see e.g. Acemoglu and Pischke, 1999, Gersbach and Schmutzler, 2001, 2006)².

¹ Training incidence is defined here as training participation rate in the 4 weeks preceding the survey of full-time employees aged between 25 and 54 years and with at least 4 weeks of tenure. The OECD indicator used here covers all aspects of anticompetitive regulation (excluding public ownership) and ranges between 0 - no regulation – to 6 - maximum regulation. The sector average of each variable has been subtracted to make comparable in a single charts figures of different industries. ² The only exception is Autor (2001) who studies firm-sponsored training in the Temporary Help Sevice (THS) industry. In his model training is provided at the time of hiring and is essentially used by THS firms as a screening and selection device. Greater product market competition increases the pressure to secure high-ability workers and the need to use training as a way to attract and select them. His model is appropriate for the THS industry, where yearly turnover rates are above 300% and therefore screening is a major problem. It can also be generalized to explain the relationship between product market competition and induction training – that is training provided at the time of hiring – in any industry. Yet, it cannot provide a general theory of the relationship between product market competition and training insofar as it has no bearing on continuous training – that is training provided after hiring – which appears to be a large share of total firm-sponsored training (see Bassanini et al. 2007 et al., for a survey).



Figure 1. The correlation between training and regulation

Note: The training participation rate refers to training taken in the 4 weeks preceding the survey of full-time employees aged between 25 and 54 years and with at least 4 weeks of tenure. The regulation indicator covers all aspects of anti-competitive regulation (excluding public ownership) and ranges between 0 - no regulation - to 6 - maximum regulation. The sector average of each variable has been subtracted to make comparable in a single charts figures of different industries. Data refer to averages for 1995-2002 for 3 1-digit sectors (Energy, Transport and Communications) and 15 countries (Norway and pre-enlargement EU excluding Luxembourg). *Sources*: OECD regulatory database and Eurostat's European Labour Force Surveys.

This view also appears to be in contrast with a standard finding in the theory of industrial organization: a firm's incentives to reduce unit costs do not depend on the size rents *per se* but on the sensitivity of rents to unit cost reductions (see e.g. Boone, 2000, and Aghion et al., 1997). Rent size can matter only indirectly, when it affects the response of rents to unit costs reductions. In particular, in the case of price competition (that is when firms set prices rather than quantities), if firms have similar production costs, it is well known that greater competition increases incentives to reduce unit costs even if rents – defined in terms of profits per unit of output – fall (see e.g. Aghion et al., 2001). This occurs because reducing costs allows reducing prices and the sensitivity of product demand to relative prices is greater, the greater the degree of competition. Greater output gains from cost reduction appear to outweigh the loss due to compression of unit rents.

In this paper we argue that a similar mechanism applies to the investment in human capital by

firms, insofar as firms pay for training only as a mean to reduce unit costs (see e.g. Stevens, 1996, Acemoglu and Pischke, 1999). We develop a model which casts the training decision in an economy characterized by imperfectly competitive product and labour markets where firms are ex-ante identical and compete in the product market by setting prices, as in Blanchard and Giavazzi (2003). We show that in equilibrium deregulation has two contrasting effects on training. On the one hand, a reduction in the barriers to entry for a given number of firms compresses profits per unit of output, and thereby tends to depress training. This is the mechanism usually stressed in the literature. On the other hand, and conditional on profits per unit of output, additional firm entry due to deregulation increases the output gains from training, thereby raising the incentive to invest in training. Output gains increase because additional training reduces the relative product price and the response of output to prices is greater, the greater the degree of competition in the product market. We use a numerical simulation to show that for reasonable values of the parameters the latter effect prevails on the former.

Our focus on the training paid and organized by firms is motivated by the fact that this is the bulk of workplace training (see Bassanini et al., 2007, for a survey on studies of training financing). We show, however, that the positive relationship between deregulation and training holds also when it is the employee who invests and bears the training costs: since additional firm entry due to deregulation increases the output gains from employing trained workers, the demand for skilled workers improves, and so does their supply.

Empirical work on product market competition and training is scarce. We are aware of only two studies on the issue and both point to a positive relationship between competition and training. Autor, 2001, shows that the Herfindhal index and training are negatively correlated in US temporary help firms, which suggests that less competition reduces training. In a multi-country study of Europe, which exploits cross country and time series variations in product market and labour market institutions, Bassanini et al, 2007, find evidence of a negative and statistically significant correlation between the index of product market regulation developed by the OECD and training intensity, thereby supporting and generalizing Autor's findings.

One potential drawback of multi-country studies is that the combination of the country and time dimensions does not allow to control for many confounding factors that might affect training and that vary across country and over time. One way to overcome this limit is to add an additional dimension to the data, as we do in the current paper. We build on the approach followed by Bassanini et al, 2007, by adding the sector as such dimension. With data which vary by country, year and sector, we can compare a treatment group, which consists of the sectors directly affected by our measure of

deregulation, with a control group, composed of those sectors which are not affected *directly* by such measure, while at the same time controlling for country and country by time specific effects. The assignment to sectors is random insofar as we can safely rule out the possibility that firms anticipating policy reform can switch sector of production. Given the costs of switching sector, we believe that this source of endogeneity is of second order of relevance.

We use the OECD database on product market regulation which has been designed to pick up regulatory reforms in traditionally heavily regulated sectors, such as transport, communication and public utilities. We consider these sectors as our treatment group, and contrast their behaviour with respect to training with the control group, which consists of the manufacturing sector, limiting our analysis to European countries. After the implementation of the European Single Market Programme (SMP hereafter) in the early 1990s, we can assume that no sector-specific regulatory reform affected the manufacturing sector, which therefore qualifies as a genuine control.³ By comparing training incidence in these sectors, we try to disentangle the effects of deregulation on training from other confounding factors, which affect both groups. To do so we match regulation data with training data from the European Labour Force Survey (ELFS) as well as several other sector-level databases, to obtain a rich sector-level database of training covariates.

Our econometric analysis confirms that reducing product market regulation increases training incidence. The estimated effects are significant. Depending on the selected measure of regulation and on the empirical specification, a 10 percent reduction of regulation increases training incidence in the exposed industries by 2.8 to 5 percent, which suggests that the positive effect on training of the higher number of firms prevails on the negative effect associated to the reduction of available rents.

One might question whether the OECD indicators can adequately capture the regulation and deregulation processes taking place in the treated industries. If yes, we would expect these indicators to positively affect industry specific profitability. We show that this is the case when profitability is measured by the observed Lerner index (defined as the average share of the value of output that exceeds variable costs, see e.g. Klette, 1999). We also decompose the marginal effect of regulation on training incidence into its effect on the Lerner index and the marginal effect of the Lerner index on training, and show that the former is positive and the latter is negative – higher profits are associated to higher rents but also to a lower number of firms, and the overall effect on training is negative.

The paper is organized as follows. In the first section we develop the theoretical model. The

³ The manufacturing sector, however, could be affected indirectly, because of the close linkage among sectors typical of modern economies.

subsequent sections introduce the empirical strategy and the data and present our estimates of the relationship between training and product market regulation. Conclusions follow.

1. The Model

1.1 Baseline model with firm-specific training

Following Blanchard and Giavazzi, 2003, and Stevens, 1996, consider a two - stage model economy where each firm produces a differentiated product using labour. The number of firms m is determined by an entry condition, which is affected by product market regulation. The logical sequence of the model is as follows: first of all, firms decide entry. In the first preparatory stage after entry, each firm invests in training and pays the training costs. In this sub-section we assume that the skills imparted by training are firm–specific⁴. This assumption will be relaxed in the next sub-section. In both the decision to enter and in the choice of how many workers to train, the employer can perfectly foresee the wages she will pay in the final stage, the level of employment L, the prices she will be able to sell her goods at and the number of firms operating in the market. In the second and final stage, and conditional on training, firms and workers bargain over wages and employment, prices are set and production occurs.

Firms in this economy share the same production and training technology, and the same elasticity of product demand. Risk neutral workers have the same reservation wage, and there are no exogenous separations of workers from firms. We show that the equilibrium is symmetric: all firms choose the same training incidence, each product price is equal to the average price, and each trained worker receives the same wage. With symmetry, in equilibrium there is no ex-post labour mobility and ex-post poaching. Firms operate the technology

$$Y_i = AL^e_i \tag{1}$$

where Y is output, L^e is employment in efficiency units, A is the productivity of labour and the subscript *i* is for the single firm. Labour consists of trained (L_T) and untrained (L_U) workers. Trained

⁴ The latter assumption is less restrictive than one might think insofar as each firm might have an idiosyncratic combination of general skills (see e.g. Lazear, 2003).

workers are skilled and untrained workers are unskilled. Since trained workers are more productive than untrained workers, employment in efficiency units is

$$L^{e}_{i} = L_{Ui} + \gamma L_{Ti}$$
^[2]

where $\gamma > 1$ is the relative efficiency of skilled labour⁵. Letting *T* be training incidence and *L* employment, $L_{Ti} = T_i L_i$ and the production function can be written as⁶

$$Y_i = AL_i [1 + (\gamma - 1)T_i]$$
^[3]

Since employment is set by bargaining in the second stage of the game, the decision on how many workers to train in the initial period is equivalent to the choice of training incidence T.

Define net and gross profits as net and gross of training costs. The characterization of the equilibrium proceeds by backward induction and starts with the decision concerning wages and prices. We assume that untrained workers do not bargain but receive the common reservation wage V (this assumption is lifted in the appendix).⁷ Trained workers, however, bargain over wages and prices with the firm. Ex-post bargaining is justified by the fact that, when firms invest in firm – specific training, workers cannot commit on ex-ante wages but re-contract after the training investment has taken place (Malcolmson, 1997). Let the wage of untrained workers be $W_U = V$ and the wage of trained workers be $W_T = W$, with $W \ge V$.

We characterize the bargaining as a cooperative Nash game, which we solve by maximizing

$$\beta \ln [(W_i - V)T_i L_i] + (1 - \beta) \ln \{P_i Y_i - L_i (W_i T_i + V(1 - T_i))\}$$
[4]

with respect to wages and employment. This is equivalent to assuming that the parties are involved in efficient bargaining. An alternative characterization would be the "right to manage" model, where the employer retains authority over employment determination. We follow Blanchard and Giavazzi in the

⁵ Total employment is defined as $L_i = L_{Ui} + L_{Ti}$.

⁶See Dearden, Reed and Van Reenen, 2006.

⁷ This assumption is consistent with estimates of Cahuc et al. (2006) for France, who find no bargaining power for unskilled and medium-skilled workers.

preference for efficient bargaining, which they argue has the advantage of capturing the possibility that firms are not operating on their demand for labour. However, we show in the Appendix that our key qualitative results are not affected if we were to choose the right to manage model.

In eq. [4] the element in brackets is the gain from a positive settlement accruing to trained workers, who have linear utility functions. This gain is weighted with the relative bargaining power of skilled labour, β , and is defined as the difference between the settled wage and the reservation wage, which accrue to skilled labour in the event of failure to reach an agreement. By definition, unskilled workers do not gain from the bargain, and are bound to their reservation wages. In the Appendix we show that our key results still hold when we allow unskilled labour to actively participate to the bargain. The element in braces is the gross nominal profit from a positive settlement accruing to the employer⁸. We assume that profits in the event of failure to settle are equal to zero⁹.

Notice that employment setting is equivalent to price setting, because labour demand is a derived demand and each firm faces the following product demand function

$$Y_i = \frac{Y}{m} \left(\frac{P_i}{P}\right)^{-\theta}$$
[5]

where $\theta = \sigma g(m) > 1$, σ is a suitable constant and g' > 0, Y is aggregate output, and P_i and P are the price of product *i* and the average price. As in Blanchard and Giavazzi, 2003, the absolute value of the elasticity of demand with respect to the relative price θ is increasing in the number of firms. This follows from the fact that an increase in the number of products associated to entry raises the elasticity of substitution between products.

The outcome of the bargain is

$$T_i W_i = \beta P_i A \left[1 + \left(\gamma - 1 \right) T_i \right] + V (T_i - \beta)$$

$$[6a]$$

$$\frac{P_i A[1+(\gamma-1)T_i]}{[W_i T_i+V(1-T_i)]} = \frac{\theta}{\theta+\beta-1}$$
[6b]

⁸ Profits are gross because training costs in the second stage are bygones.

⁹ Failure to settle disrupts the production process, so that no production occurs and the parties separate. When training is firm – specific this separation implies that the accumulated skills are lost.

Simple manipulation of these two conditions yields¹⁰

$$\frac{P_i}{P} = \frac{\theta}{\theta - 1} \frac{V}{PA[1 + (\gamma - 1)T_i]}$$
[7]

We next turn to the initial preparatory period, when employers decide how many workers to train. Let the real cost of training per employee be

$$c(T_i) = \frac{\mu T_i^2}{2}$$
[8]

a convex increasing function of training incidence. This assumption captures decreasing returns in the production of human capital and rules out corner solutions for optimal training incidence.¹¹ Using [5] and [6a] in the definition of net real profits Π ,¹² we obtain

$$\Pi_{i} = \left\{ \frac{1-\beta}{\theta-1} \frac{V}{PA(1+(\gamma-1)T_{i})} - \frac{\mu T_{i}^{2}}{2A(1+(\gamma-1)T_{i})} \right\} \frac{Y}{m} \left(\frac{\theta}{\theta-1}\right)^{-\theta} \left(\frac{V}{P}\right)^{-\theta} \left[A(1+(\gamma-1)T_{i})\right]^{\theta}$$
[9]

The term in braces on the right-hand side represents net real profits per unit of output π_i , while the product of all the other terms on the right-hand side represents output Y_i . Since the marginal variation of real profits as a result of additional training is given by

$$\frac{\partial \Pi_i}{\partial T_i} = Y_i \frac{\partial \pi_i}{\partial T_i} + \pi_i \frac{\partial Y_i}{\partial T_i} = Y_i \left[\frac{\left(-\mu T_i\right)}{A\left(1 + (\gamma - 1)T_i\right)} - \frac{(\gamma - 1)\pi_i}{\left(1 + (\gamma - 1)T_i\right)} \right] + \pi_i \frac{\theta(\gamma - 1)Y_i}{\left(1 + (\gamma - 1)T_i\right)}$$
[10]

¹⁰ Employment is given by $L_i = \frac{Y_i}{A[1+(\gamma-1)T_i]} = \frac{Y}{m} \frac{1}{A[1+(\gamma-1)T_i]} \left(\frac{P_i}{P}\right)^{-\theta}$

¹¹ The assumption of a quadratic is made for simplicity, and can be justified by assuming that, inter-alia, workers are heterogeneous in terms of training costs, with uniformly distributed training costs (see section 1.2). The analysis below remains valid, however, for any weakly convex function.

¹² That is, nominal profits divided by the average price.

the first-order condition for a maximum with respect to $T_i (\partial \Pi_i / \partial T_i = 0)$ yields¹³

$$(\theta - 1)A(\gamma - 1)\pi_i = \mu T_i$$
[11]

Training is increasing in net real profits per unit of output π_i and, conditional on π_i , is decreasing in the training cost parameter μ and increasing in the difference between the productivity of skilled and unskilled workers $A(\gamma - 1)$ as well as in the elasticity of substitution θ . The latter effect comes from the fact that the output gains from training are increasing in θ . This occurs because training increases productivity, relative prices are decreasing in productivity (see eq. [7]) and the response of output to relative prices is greater, the higher is θ .

Notice that the positive relationship between profitability π_i and training only holds for a given number of firms and for given θ . However, since θ cannot be given in the long run, but is negatively related to profitability, the overall relationship between π_i and T_i can take either sign.

Substituting out π_i in [11] with its expression in terms of T, V and other parameters we obtain

$$T_i^* = \frac{-\mu \pm \sqrt{\mu^2 + 4\mu(\gamma - 1)^2 \frac{V}{P}(1 - \beta)\frac{1 + \theta}{2}}}{\mu(\gamma - 1)(1 + \theta)} > 0$$
[12]

Since both V and the parameters γ , θ , μ and β do not vary across firms, it must be that $T_i^* = T^*$, implying that all firms select the same training incidence. By implication, equation [7] implies that at the optimal level of training firms have the same relative price. Since in general equilibrium we cannot have that all firms have a relative price above or below 1 (see Blanchard and Giavazzi, 2003), it must be that $\frac{P_i}{P}$ is equal to 1, which yields

$$\frac{V}{P} = \frac{\theta - 1}{\theta} A \left[1 + (\gamma - 1)T \right]$$
[13]

where we drop hereafter the subscript *i*. Using [13], [5] and [6a] in the definition of profits, and

¹³ The second order conditions for a maximum hold.

imposing the general equilibrium condition on prices, the equilibrium number of firms is determined by the condition that net profits per unit of output π must be equal to the cost of entry per unit of output ρ

$$\pi = \frac{1-\beta}{\theta} - \frac{\mu T^2}{2A[1+(\gamma-1)T]} = \rho$$
[14]

where $\frac{1-\beta}{\theta}$ is gross real profits per unit of output. Blanchard and Giavazzi, 2003, use a similar convenient specification for the cost of entry. In the Appendix we show that our results still hold when we specify more conventionally the cost of entry as a fixed cost, rather than as a cost proportional to output.

Conditional on training, a fall in the costs of entry increases the number of firms and θ . As a consequence, profits per unit of output fall until the arbitrage condition [14] is satisfied. A reduction in ρ can be brought about by liberalisation reforms lowering regulatory barriers in the product market. For instance, one can assume that $\rho = f(R)$, where *R* measures the stringency of regulatory barriers and $\partial f / \partial R > 0$. Using [14] into [11] to eliminate profits per unit of output we obtain

$$\mu T = (\theta - 1)A(\gamma - 1)\rho \tag{15}$$

Equations [14] and [15] describe two schedules in the (T, θ) plane: the schedule TT associated to [15] implies a positive relationship between training incidence and the number of firms¹⁴ (see Figure 2). The reason is that, conditional on net profits per unit of output, the output gains from training are larger the larger the elasticity of substitution between products (see eq. [11]). On the other hand, the schedule MM associated to [14] suggests a negative relationship between *T* and θ . Conditional on net profits per unit of output, the greater the training, the greater the gross profits that are required to avoid losses. In turn, this implies that, if net profits are fixed by entry barriers, the greater the training the smaller the number of firms that can survive in equilibrium without making losses.

We establish the following

¹⁴ Recall that
$$\frac{\partial \theta}{\partial m} = \sigma g'(m) > 0$$
.

Lemma. The long run equilibrium exists and is unique if the following two conditions hold:

$$\rho \le 1 - \beta$$

$$\frac{A(\gamma - 1)\rho + \mu}{A(\gamma - 1)\rho} \ge \frac{2A\gamma(1 - \beta)}{\mu + 2A\gamma\rho}$$

Proof: Equations [14] and [15] describe two schedules in the (T, θ) plane: the schedule TT associated to [15] has a positive slope and the schedule MM associated to [14] has a negative slope. Training incidence tends to zero as $\theta \rightarrow 1$ in [15] and to a non-negative number in [14] if $\rho \leq 1-\beta$. Since incidence ranges between 0 and 1, an equilibrium exists if the two schedules intersect for $0 \leq T \leq 1$.



Figure 2: The relationship between θ and T

The condition $\frac{A(\gamma-1)\rho + \mu}{A(\gamma-1)\rho} \ge \frac{2A\gamma(1-\beta)}{\mu+2A\gamma\rho}$ guarantees that this is the case by imposing that at T = 1 the value of θ on the TT line is at least as large as the value on the MM line. When the two conditions are satisfied the two schedules intersect once and only once in the relevant domain of the two variables. QED

We can now establish the following proposition concerning equilibrium comparative statics:

Proposition. Subject to the conditions of the above lemma, a reduction in entry barriers – which corresponds to a reduction in the parameter ρ – increases training incidence if

$$\frac{1-\beta}{\theta(\rho)}\frac{\theta(\rho)-1}{\theta(\rho)} < \rho \le \frac{1-\beta}{\theta(\rho)}$$
[16]

and reduces training incidence if

$$0 < \rho < \frac{1 - \beta}{\theta(\rho)} \frac{\theta(\rho) - 1}{\theta(\rho)}$$

Proof: total differentiation of [14] and [15] yields

$$\Sigma_1 dm + \Sigma_2 dT = \Sigma_5 d\rho$$

$$\Sigma_3 dm + \Sigma_4 dT = \Sigma_6 d\rho$$

where

$$\Sigma_{1} = \sigma g'(m)(\gamma - 1)\rho A \quad \Sigma_{2} = -\mu \qquad \qquad \Sigma_{3} = -\frac{1 - \beta}{\sigma g(m)^{2}} g'(m) \quad \Sigma_{4} = -\frac{2\mu T + \mu T^{2}(\gamma - 1)}{2A[1 + (\gamma - 1)T]^{2}}$$

$$\Sigma_{5} = -(\sigma g(m) - 1)(\gamma - 1)A \qquad \qquad \Sigma_{6} = 1$$

Since the determinant of the Jacobian is negative when $\theta < +\infty$ and $\rho > 0$, $\frac{dT}{d\rho} < 0$ if $\Sigma_1 \Sigma_6 - \Sigma_3 \Sigma_5 > 0$, or

$$\frac{1-\beta}{\theta(\rho)}\frac{\theta(\rho)-1}{\theta(\rho)} < \rho$$

Non-negative profits also imply – see [15] – that $\rho \leq \frac{1-\beta}{\theta(\rho)}$. Therefore $\frac{dT}{d\rho} < 0$ if

$$\frac{1-\beta}{\theta(\rho)}\frac{\theta(\rho)-1}{\theta(\rho)} < \rho \le \frac{1-\beta}{\theta(\rho)}$$

Clearly, $\frac{dT}{d\rho} > 0$ if $\frac{1-\beta}{\theta(\rho)} \frac{\theta(\rho)-1}{\theta(\rho)} > \rho$. QED

We also establish the following corollary

Corollary. A reduction in the barriers to entry increases the number of firms *m*.

Proof. Follows from the proof above and from the fact that $\Sigma_5 \Sigma_4 - \Sigma_2 \Sigma_6 > 0$.

In comparative statics terms, the effect on training incidence of product market deregulation bringing about a reduction in entry costs is graphically illustrated in Figure 3, where continuous lines refer to the initial equilibrium and dashed lines to the new equilibrium. While the effect of such a deregulation on the number of firms is not ambiguous, the effect on training depends on the relative shift of the two curves. Taking as given the training incidence of each firm, a reduction in the barriers to entry increases the number of firms, thereby shifting the MM schedule outwards – see equation [14]. This, in turn, increases training incidence along the TT schedule since, conditional on net profits, output gains from training are greater – see equation [15]. However, for a given number of firms, lower entry barriers also rotate the TT schedule downwards,¹⁵ because they reduce net profits per unit of output – see equations [10] and [15]. This reduces training incidence. The overall effect on *T* is ambiguous, but is positive if condition [16] holds.

Condition [16] is less likely to hold when entry costs are already low or the number of firms is high ($\theta \rightarrow \infty$). However, for reasonable values of the parameters it holds even for relatively low values of ρ . To illustrate this numerically, we assume a linear relationship between the cost of entry and regulatory barriers, as measured by regulatory indicators (see next section). We then set the configuration of parameters in such a way that, when the ratio of the measure of barriers to entry to its maximum possible value $(1-\beta)$ is equal to the observed median ratio in the sample for which we have training and regulation data (3 industries, 1995-2002, 15 countries, see Figure 1 above), we obtain approximately an optimum training incidence equal to the observed median training incidence. This ratio is equal to 0.62 according to our indicators. Assuming with no loss of generality that A=1, we consider all possible combinations of β , γ and μ such that for $\rho = 0.62*(1-\beta)$ we obtain that optimal training incidence is equal to the median level that we observe in our data (8.0%).¹⁶ With this choice of parameters, a deregulation which cuts ρ increases training for most of the range of variation of ρ . For instance, for any value β and realistic values of γ , say $\gamma \leq 1.7$ – which implies that the productivity of trained workers is no greater than 170% the productivity of untrained workers –

¹⁵ The barycentre of the rotation is the point (1,0).

¹⁶ Where training incidence is defined in terms of the participation rate as in Figure 1. A similar picture (see appendix) can be obtained if we consider the stock of training computed by perpetual inventory method (see next section for the method of calculation), which corresponds better to the concept of training incidence developed in the model.

deregulation raises training if $\rho/(1-\beta)$ is at least as large as 0.146 (see Figure 4),¹⁷ a low threshold which has rarely been attained in historical perspective, and which is not attained by about 7% of the observations for which we have data.



Figure 3: The effect of reducing barriers to entry

Even more, $\frac{dT}{d\rho} \cong 0$ in a relatively large region, and it starts getting significantly greater than zero only for values close to $\rho/(1-\beta) = 0.06$, that corresponds to less than 3% of the observations for which we have data. Conversely, for values above 0.4, which corresponds approximately to the first quartile in our data, the relationship between barriers to entry and training stocks is negative and very close to linear.

¹⁷ Figure 4 illustrates this for $\beta = 0.5$. For any other value of β in the interval [0,1), the admissible range of variation of regulation differs. Yet, by rescaling the ρ -axis, one obtains very similar equilibrium manifolds as in Figure 4.



Figure 4: The relationship between ρ and T with $\beta = 0.5$, $1.05 \le \gamma \le 1.7$ and μ such that median training rates correspond to median regulation levels

1.2 General training: training versus hiring skilled labour

In the economy described so far, each firm invests in firm – specific training and is willing to pay the necessary training costs. Suppose now that skills are at least partly general and that at the end of the initial period – before the bargain occurs – firms have the option of hiring already skilled labour from the labour market or from other firms (*poaching*). If hiring were costless and hired workers were as productive as workers trained in-house, no firm would be willing to train and bear the training costs. However, hiring skilled labour in an imperfectly competitive labour market is costly, either because skills are not fully transferable or because of the presence of frictions and information asymmetries. For

example, one can imagine that hiring skilled labour requires a costly – both in terms of time and resources – screening activity in order to distinguish between skilled and unskilled applicants and to measure the skills of potential hires. Assuming that all firms have the same hiring costs, firms decide whether to train or not by comparing marginal training and hiring costs.

The results in Section 1.1 hold when the marginal cost of training is lower than the marginal cost of hiring for any value of training incidence. In this case, firms' willingness to pay for training is justified because labour market frictions – including search and informational asymmetries – substantially reduce the transferability of general skills from a firm to another, as discussed by Acemoglu and Pischke (1999). Consider now the opposite case, where hiring is less costly than training. With no heterogeneity in the technology and in the costs of hiring and training, all firms will prefer to hire skilled labour than train unskilled labour. But with no training by firms there can be no hiring of skilled labour, unless workers themselves are willing to bear the training costs.

We study this case by assuming that risk neutral workers who invest in training acquire similar skills but pay an idiosyncratic training cost ξ_i , which is uniformly distributed in the population with constant density ψ .¹⁸ Then the proportion of workers investing in training consists of those individuals with training costs that are lower than or equal to the expected real gain from training $\frac{W-V}{P}$, and the training supply curve is

$$\frac{W-V}{\psi P} = T \tag{17}$$

suggesting that training incidence increases with the skilled wage gap.

When workers differ only in their training costs and training is general in nature, wages W are determined by the supply and demand for skilled labour. In the second stage each firm takes wages as given and selects employment and the percentage of skilled employees to maximize real profits

¹⁸ The results obtained in the previous subsection for firm-specific training and homogeneous training costs can be easily obtained with heterogeneous uniformly distributed costs if: i) firms do not know individual training costs at the time of hiring but they know the distribution of these costs, so that by the law of large numbers each firm faces the same distribution of training costs independently of its size; ii) upon hiring training costs are revealed and firms first train workers with lower costs. Under these assumptions the analysis of section 1.1 can be replicated by simply replacing μ with ψ .

$$\Pi_{i} = \left\{ AL_{i} \left[1 + (\gamma - 1)T_{i} \right] \right\}^{1 - \frac{1}{\theta}} \left(\frac{Y}{m} \right)^{\frac{1}{\theta}} - \frac{W}{P} L_{i}T_{i} - \frac{V}{P} L_{i}(1 - T_{i})$$
[18]

The first order condition with respect to training is

$$\left(1 - \frac{1}{\theta}\right) \frac{P_i}{P} A L_i(\gamma - 1) = L_i(\frac{W - V}{P})$$
^[19]

Imposing the equilibrium condition $\frac{P_i}{P} = 1$ and using [17] in [19] we obtain that training incidence is given by

$$T = \left(1 - \frac{1}{\theta}\right) A \frac{\gamma - 1}{\psi}$$
[20]

The above equation indicates that, when workers invest in training and skills are general, a deregulation of the product market which raises the number of firms and the elasticity of product demand θ generates higher training incidence because it increases the marginal benefits of training accruing to firms and the demand for skilled labour. Higher demand generates in turn higher wages for skilled labour, which induce a higher supply of skills. We conclude that empirical evidence showing that regulation reduces training incidence is consistent both with an equilibrium discussed in subsection 1.1, where firms train and bear the training costs, and with an alternative equilibrium where workers bear the training costs and firms hire skilled labour from the market.

2. The Empirical Model

In the empirical application, we are interested in investigating whether changes in regulation affect training incidence, measured as the proportion of workers receiving training. Equations [14] and [15] generate in implicit form a map from entry costs ρ to training incidence *T*, which is plotted in Figure 4 for a selected configuration of parameters. To the extent that the relationship between entry costs ρ and the degree of stringency of regulatory barriers is monotonic, this map is also from regulatory barriers *R* to training incidence *T*. As described in detail in the data section below, we do not

dispose of a direct measure of entry costs. Yet, given that our ultimate interest is establishing an empirical relationship between regulation and training, we can estimate directly the implicit equilibrium mapping between R and T brought about by the model.

Alternatively, since in the long-run equilibrium entry costs are equal to (net) real profits per unit of output, we can use a measure of profitability, such as the Lerner index, to proxy entry costs. In this case, the relationship between deregulation and training consists of two components: the effect of profitability on training and the effect of product market regulation on profitability (entry costs). However, the problem with any measure of profitability is that it is endogenous, as productivity shocks which affect training also influence profits. Fortunately, and letting aside political economy considerations, regulation can be assumed to be exogenous and the degree of stringency of regulatory barriers can be used as an instrument for the measure of profitability.¹⁹

Our regulatory indicators and profitability measures vary by sector, country and over time. Therefore, we collapse our data on training and additional controls at the same level of aggregation. As discussed in the previous section, for most of our sample a monotone (negative) relationship between entry costs (regulatory barriers) and training prevails. We can therefore estimate the following empirical counterpart of the theoretical model:

$$T_{ict} = \lambda_0 + \lambda_1 X_{ict} + \lambda_2 Y_{ict} + \varepsilon_{ict}$$
[21]

where the vector X includes a vector of controls, such as average age, education and firm size, Y is the selected measure of regulation or profitability, the subscript i is for the industry, c is for the country and t is for time.

The linear specification in [21] can be problematic when the dependent variable is fractional (see Wooldridge, 1999). Following Papke and Wooldridge (1996), we assume that the conditional mean is a logit function G of the independent variables and consider the following transformed generalized linear model (GLM) as an alternative to (21):

$$T_{ict} = G(\lambda_0 + \lambda_1 X_{ict} + \lambda_2 Y_{ict}) + \varepsilon_{ict}$$
[22]

¹⁹ Regulation might be endogenous if deregulation tends to occur where productivity growth or innovation are greater and training is correlated with these variables (see e.g. Duso and Röller, 2003). Although we believe that this is unlikely to

that we estimate using a quasi-maximum likelihood estimator (QMLE), where the quasi-likelihood function is the binary choice log likelihood.²⁰ We postulate that the error term is as follows

$$\varepsilon_{ict} = \xi_{ic} + \xi_{it} + \xi_{ct} + \omega_{ict}$$
[23]

where ξ_{ic} is a country by industry effect, ξ_{it} is an industry by time effect, ξ_{ct} is a country by time effect, and ω_{ict} is a standard disturbance. We control for these unobserved effects by including in the specification country by sector, country by year, and sector by year dummies. The country by sector dummies capture cross country differences in the structure of each industry, including differences in the parameters σ , γ , β and A; the sector by year effects capture the time varying differences in trend growth between affected industries (treated group) and industries not affected directly by deregulation (control group); the country by year dummies absorb country-specific macroeconomic effects, countrywide changes in policy (notably training policy and nation-wide regulation, on which we have no data see below) as well as changes in the routing of the questionnaire and/or the exact formulation of the training question.

Our key interest lies in estimating the coefficient λ_2 , which measures the relationship between product market regulation and training. A negative estimate of λ_2 would confirm that a negative relationship between regulation and training prevails. Strictly speaking, however, our theoretical model suggests that this coefficient is positive for low levels of regulation and negative for higher values. We can therefore try to capture this bell-shaped pattern by fitting a quadratic in our regulatory indicators. Yet, since we do not have data on nation-wide aspects of regulation affecting all sectors, we will have to do a number of arbitrary assumptions to estimate these quadratic specifications, and results obtained from them must be viewed as a tentative extension.

One can argue that the training concept developed in the model corresponds to steady state training stocks. Yet, we only have data on training flows (see next section). However, given that

seriously affect estimates, we partially control for this channel by adding to some of our specifications, as additional covariates, R&D intensity, productivity levels and growth and the investment rate.

²⁰ Papke and Wooldridge (1996) show that QMLE estimators of this kind yield consistent estimates of equation [22] independently of any assumption on the error term, for which a robust variance estimator can be easily devised. In addition, in contrast to the more classical WLS estimation of a linear model with log-odds transformation of the dependent variable, the GLM specification does not require adjustment for boundary values (such as zeros) and can be estimated when fractional data are obtained by sample averages in samples of unknown size that cannot therefore be used to construct weights, as is our case.

training stocks and training flows are likely to be positively correlated, we can re-specify our empirical model in terms of the training flow τ , by simply substituting it for *T* in equation [21]. Alternatively, we can construct training stocks from training flows by following a methodology similar to Conti (2005) and Dearden et al. (2006). In particular, we assume a common depreciation rate ($\delta = 0.15$) and a steady state rate of training growth *g* equal to the sample average growth rate of training flows²¹, and reconstruct initial conditions under the assumption that steady state growth occurs at the beginning of the sample, which implies $\tau_1/(\delta + g) = T_0$, where τ_1 is the training flow in the first period and T_0 the training stock in the initial period. Finally, training stocks after missing years are constructed by assuming steady state growth in those years. Insofar as these data are reconstructed, we prefer to specify our model in terms of flows and use training stock data only in a sensitivity analysis.²²

Specifications [21] and [22] assume that, conditional on the vector X, product market regulation variables are the only institutional variables that can vary by country, year and sector, and that institutional confounding factors are fully accounted for by the combination of country by year, country by sector and sector by year dummies. While this is plausible, we cannot rule out the possibility that variables measuring labour market institutions at the same level of detail as regulation variables could affect training incidence. If this is so, failure to account for these effects could erroneously attribute them to changes in product market regulation. Therefore, we also experiment with specifications that augment the vector X with available measures of labour market institutions.

3. Data

We use three main sources of data: a) an OECD database on training and other labour market variables; b) OECD regulatory indicators for seven non-manufacturing industries (electricity, gas, air transport, road transport, railways, post and telecommunications); c) additional sector-level information on output, physical capital etc...) available in the OECD STAN Family databases and the companion 60-industry database of the Groningen Growth and Development Centre.

The OECD database on training is drawn from the EU Labour Force Surveys. It contains information on training and a number labour market variables (namely age, gender, education, parttime/full-time status, occupation, industry, firm-size, tenure, whether the contract is temporary or

²¹ In the steady state flows and stocks grow at the same rate. In country/sector units where a decrease of training flows is observed, the steady state growth rate is set to zero.

permanent, whether the activity is in the country of residence, participation in training, type of training and training duration) for employed workers of 23 European countries from 1995 to 2002 (with many missing values, corresponding to countries and years where questions on training were not administered or data on training are unreliable). Data have been collected in the second quarter of each year (March in most countries). Quantitative variables (such as tenure or firm size) are divided into categories (see the appendix for more details). As regards to age, we dispose of categories covering five-year intervals. We then reconstruct an ordinal variable by applying to all observations in each category the mean age of the category. Data are semi-aggregated insofar as organized by cells. Each cell corresponds to a combination of categories. Available cells cover all non-empty combinations with one category for each variable. Population weights are reported for each cell.

Training data refer to participation in any education or training course in the 4 weeks preceding the interview (1 week for France). Data on the type of training and its length are often missing. For this reason, we do not use this information. In order to avoid that initial and close-to-retirement education confound the information on workplace training, we limit our analysis to full-time employees with at least 1 month of tenure, aged between 25 and 54 years, and working in their country of residence. Descriptive statistics on training are available in the Appendix.

We collapse our data on training and selected other labour market variables (education, age, gender and firm size) at the level of sectors. Industries are available at the 2 digit level of the NACE rev.1 classification (that, at the 2 digit level, corresponds to the ISIC rev. 3, with extremely few exceptions) for most countries and years in manufacturing. In services, they are available at a slightly more disaggregated level than 1 digit of NACE rev. 1. However, since only NACE 1970 is available for 1992 and for certain country-year pairs, we are obliged to aggregate a few industries in order to construct our sector-level database. The final list of industries is available in the Appendix.

We have access to detailed OECD indicators on anti-competitive product market regulation for seven 2 or 3 digit non-manufacturing industries. Data are available on an annual basis and span from 1975 to 2003 for 21 OECD countries. Following Alesina et al. (2005) we use these data to construct time-series indicators of regulatory barriers for three more aggregate industries (utilities, transport, and communication services), for which we have training data (see above). Detailed regulatory indicators concern sector-specific entry barriers, public ownership, the market share of the dominant player(s) when relevant (in the telephone, gas and railroad sectors), vertical integration in network industries and

 $^{^{22}}$ In the sensitivity analysis we will consider also three other measures of the training stock obtained by varying construction hypotheses.

price controls when relevant (in the road freight industry). Outside the scope of these indicators are nation-wide aspects of regulations applying to all industries, such as administrative barriers to entrepreneurship (administrative barriers on start-ups, general features of the licensing and permit system, etc...), since these data are not available in time-series in the OECD database.

Available indicators vary between 0 and 6 from the least to the most regulated. Entry barriers cover legal limitations on the number of companies and rules on vertical integration of network industries. A value of 0 corresponds to free entry. By contrast, a value of 6 applies when entry is severely restricted. Public ownership measures the share of equity owned by central or municipal governments, and takes a value of 0 in the case of no equity and a value of 6 in the case of full ownership. All other indicators are similarly defined. More details on these indicators are available from Nicoletti et al. (2001), Alesina et al. (2005) and Conway and Nicoletti (2006).

We construct our aggregate indicators following the same methodology of Alesina et al. (2005). This involves two steps. First, separate indicators of barriers to entry, public ownership, market structure, vertical integration and price controls for each of the seven industries are averaged to obtain two coarser (and partially alternative) indicators: BEVI, which summarizes barriers to entry (comprising legal restrictions and vertical integration) and REGNO, which includes all dimensions except public ownership²³. As our model applies explicitly to barriers to entry we expect BEVI to be related to training. The same might apply to REGNO insofar as the presence of price controls and the absence of barriers to concentration can, to a certain extent, be seen as additional barriers to start-ups. Second, the same indicators for the three more aggregated industries are obtained by simple averaging the values of the corresponding sub-industries.

Once the two indicators of regulation are matched to our training data we obtain 312 country by sector by time non-missing observations concerning three (typically regulated) service industries for 15 European countries and a maximum of 8 years.²⁴ Yet, these industries account for a small share of total employment (about 7.5% in 2002). Moreover, in the event that reforms in these three sectors have occurred almost simultaneously, the effect of the variation in regulation on training incidence risks to be swept away once country per year dummies are included in the empirical analysis.

²³ A third indicator, REGPO, which summarizes the degree of public ownership, is also considered. Specifications augmented by this indicator are estimated as a robustness check. This indicator however turns out insignificant without affecting significantly the coefficients of other co-variates. The lack of significance of this indicator is consistent with our model where public ownership plays no role. In addition this is also consistent with the evidence that suggests that public sector employees receive no less training than their private sector counterparts (see e.g. Bassanini et al;, 2007).

²⁴ Since the exact month of each regulatory reform is not known and might well be subsequent to the second quarter of the corresponding year, each regulatory indicator is lagged one year.

To circumvent this problem, we add manufacturing industries to our dataset. For these industries, regulation concerns essentially administrative burdens, limitations to foreign direct investment as well as barriers to trade, at least in European countries. Now, only the last two barriers can be considered to be sector-specific. But for them, due to the coming into action of the Single Market Programme (SMP) in 1992, it can be assumed that their time profile is flat since at least 1994 for the 12 countries that were EU members in 1992 (see e.g. Bottasso and Sembenelli, 2001).²⁵ The same argument can be applied to Austria, Finland, Norway and Sweden from 1995 (see e.g. Baldwin et al., 1996, and Gullstrand and Johansson, 2005).²⁶ This is equivalent to assume that – since 1994 for the majority of countries and since 1995 for a few countries - regulation in manufacturing has been equal to an arbitrary constant, which we control for with country by industry dummies. In sum, we construct an extended dataset starting from the three non-manufacturing industries by adding manufacturing and by dropping pre-SMP years. In practice, this is equivalent to using a difference in difference estimator, where manufacturing sectors are used as the control group and services are the treated group. We end up with a sample composed of 15 countries and 12 industries for a maximum of 8 years for each country-industry pair, and for a total of 1236 observations once observations with missing information on training is excluded.

As discussed above, ideally we would like to estimate a bell-shaped relationship between regulation and training. However, strictly speaking this is impossible in our data, since we do not have a time-series for those nation-wide aspects of regulation that apply to all sectors (such as administrative barriers to start-ups). In specifications such as [21] this component of regulation is controlled for by country by time dummies. However, this is no longer the case in specifications with a quadratic. On a tentative basis we can add the nation-wide indicator of administrative barriers to start-ups in 1998 to our sector-specific indicators of regulation, assuming the latter to be 0 in manufacturing, so as to obtain a reconstructed indicator of regulatory barriers that is more comparable across countries. Yet this indicator will miss the effect of administrative reforms that took place during the years 1995-2002.

As hinted at above, we consider also the observed Lerner index as a measure of unit profitability in real terms. In our data the Lerner index L is defined as the difference between the value

²⁵Bottasso and Sembenelli (2001) report that, on average, 75% of the measures implied by the SMP agreement were already transposed into national legal systems at the time when the SMP came into action, and that virtually all measures were transposed shortly after.

²⁶ According to the first editions of the Single Market Scoreboard (EC, 1997, 1998), by 1997 Finland, Norway and Sweden were among the best performing countries as far as transposition of EC directives is concerned. Only Austria appeared to lag behind, but its gap with other EU countries was closed in 1998. For this reason we check that our results are robust to exclusion of Austria prior to 1998.

of output and total intermediate, labour and capital costs, normalised by the value of output.²⁷ All the relevant data, except interest rates, are from the OECD STAN database (current and previous versions).²⁸ Following Griffith et al. (2006), we calculate the cost of capital assuming that capital flows freely across borders so that all countries face a world interest rate, for which we use the US long-term interest rate taken from the OECD EO Database. This measure is, however, available only for fewer observations (1120) and completely missing in one country (Ireland).

The other additional relevant covariates are taken from the OECD STAN and related databases. First, one can imagine that growing businesses will have a greater propensity to train than downsizing businesses, insofar as in the former the proportion of new hires in need of induction training is likely to be greater,²⁹ while in the latter the proportion of dismissals, upon which employers will be unable to recoup the cost of training, is likely to be greater. Therefore we include the logarithm of employment growth as a further control. Second, there are good reasons to think that training might vary over the business-cycle. For instance, according to Hall (2000), re-organisations take place during slack periods when the cost of foregoing production to re-allocate resources is smaller. The case studied by Hall concerns creation/destruction of job matches and search. However, it can well apply to internal reorganization, which usually requires long periods of adaptation, learning and training before becoming again fully efficient (see also Jovanovic, 2006). In support of such a view, Sepulveda (2002) finds that on-the-job training is counter-cyclical using data from the US National Longitudinal Survey of Youth. To control for sector-specific business cycles we construct log employment and log worked hours gaps by subtracting to each of these variables their filtered time-series obtained applying an Hodrick-Prescott filter with standard parameters.³⁰ Third, we consider the possibility that any relationship between training and entry costs be due to the relationship of the latter with other intangible investment

²⁷ This computed index is equivalent to the price-cost margin under the assumption of perfect competition and constant returns to scale (see Klette, 1999, for a discussion). In principle, violation of these assumptions might induce biases, and estimations from production or cost functions would be desirable. Yet, estimated mark-up cannot vary simultaneously by country, industry and year. In addition, our Lerner index will be treated as an endogenous variable and instrumental variables will deal with the possibility of systematic measurement error. For these reasons we prefer to follow Aghion et al. (2005) and use a computed Lerner index. ²⁸ Capital stocks in nominal terms are obtained by multiplying nominal value added by the ratio of capital stock in volume

terms obtained through perpetual inventory method and value added in volume terms.

²⁹ Yet, given that induction training is likely to occur in the very few weeks after hiring and we exclude workers with less than one month of tenure, we probably already control for part of this effect.

³⁰ We exploit here the advantage of having reliable information on employment and hours. In fact, one can expect the countercyclical pattern of training to be more important when labour hoarding dominates employment adjustments, particularly during slowdowns. However, we check that our results are robust to substituting a more classical output gap for employment and hours gaps.

by including the logarithm of R&D intensity.³¹ Finally, one might expect that the effects of deregulation are fully realised with a certain delay and/or that, particularly in certain manufacturing industries, globalisation is increasing the competitive pressure on businesses, particularly to improve production quality, independently of regulation. To account for this possibility, we include in [21] and [22] the logarithm of the import-weighted industry-specific real exchange rate, taken from OECD (2007).³²

The impact of nation-wide institutions, when homogeneous across sectors, is controlled for in equations [21] and [22] by country per year dummies. However, certain labour market institutions might not have the same impact on training in all sectors. More specifically, Haltiwanger et al. (2006) and Micco and Pages (2006), convincingly suggest that the impact of lay-off regulations on job turnover varies according to the natural propensity of industries to adjust their labour input. They show that almost all the variation in the cross-country/cross-sector distribution of job turnover can be explained by the distribution of job turnover in the United States (that is the OECD country with the least regulated labour market) and country dummies, and that the remaining variation can be explained by an interaction between a country-specific indicator of regulatory stringency and US job turnover rates by sector. Bassanini and Venn (2007) use the same methodology to explore the impact of lay-off regulations on productivity growth. We use the job turnover rate (TURN) in the US from Haltiwanger et al. (2006) and interact it with the OECD aggregate measure of employment protection legislation (EPL), so as to obtain an indicator of EPL impact that varies by country, sector and time. Union power might also vary along these three dimensions. In order to capture this effect we use data on union density from Ebbinghaus and Visser (2000). However, these data are available only for macro-sectors. Therefore we cannot do anything better than attributing their macro-sector averages to each subsectors.

Exact variable definitions, sources and sample statistics are provided in the Appendix. Since ELFS data are collected early in the calendar year, all non-ELFS data, which usually refer to yearly averages or unknown months, are lagged one year.

³¹ We have experimented also the investment rate, drawn from the OECD STAN database, and the level and growth of productivity, drawn from the GGDC 60-industry database, to control for possible endogeneity of regulation with respect to productivity. However, none of these controls turns out significant and they have no impact on estimated coefficients. ³² We also experiment with import penetration with virtually identical results. Yet, while industry-specific exchange rates,

³² We also experiment with import penetration with virtually identical results. Yet, while industry-specific exchange rates, by depending only on imports at a specific date preceding the sample, can be assumed as exogenous, given that double-dimension dummies are added to the specification, import penetration ratios are clearly endogenous.

4. Empirical results

We start our analysis by examining the association between regulation and training participation at the industry level. We estimate linear specifications (eq. [21]) with the dependent variable expressed in terms of training flows by OLS (Table 1, Panel A) and the corresponding GLM specifications (eq. [22]) by QMLE (Table 1, Panel B). Each Panel in Table 1 is organized in five columns: the first column includes only the product market regulation indicator and (bi-dimensional) fixed effects, which appear in all the columns; column (2) also includes gender, education, the log worked hours gap and the import weighted real exchange rate;³³ columns (3) to (5) consider specifications augmented with further controls which turn out insignificant or weakly significant. Column (3) adds age, firm size, and employment growth; column (4) the logarithm of R&D intensity; and column (5) industry-varying indicators capturing industry-specific effects of labour market institutions. Table 2 replicates the same specification using BEVI in alternative to REGNO.

In the two tables the association between regulation and training is always negative and statistically significant. Training incidence is significantly lower when the share of low educated individuals – with ISCED less than 3 – is higher, a standard result in the training literature (see Bassanini et al, 2007). Consistently with the finding of Sepulveda (2002) we also find that training incidence is countercyclical. Employment growth is positively associated to training but its coefficient is very imprecisely estimated. Furthermore, the import weighted real exchange rate is negatively related to training in a (weakly) significant way, yielding some support to the idea that, for the tradeable sector, globalisation can have an additional effect on training independently of deregulation.

There is some evidence that training incidence is higher in industries employing more women, a result in line with the literature as regards to Europe (see Bassanini et al., 2007 for a survey), and no evidence that age, the industry's firm size distribution and employment growth and the labour market variables matter for training. When log R&D intensity is included to control for investment in intangibles, regulation remains significant, while log R&D intensity appear to attract a negative coefficient, although only weakly significant.³⁴ Finally, union density appears to be unrelated to training while EPL do not appear to have a significantly greater effect in high turnover industries.

³³ As short- and long-run effects of the exchange rate on trade usually differ, import weighted real exchange rates are lagged one extra time. We also experimented with a 3-year moving average with virtually the same results.

³⁴ The negative sign of the coefficient on R&D intensity might look surprising. Yet this is consistent with the evidence of lack of complementarity between R&D and training expenditures provided by Ballot, Fakhfakh and Taymaz (2001).

Table 1. Estimates of training as function of the index of product market regulation REGNO, which excludes public ownership. LS

Panel A: Linear sp	pecification	estimated	by	OL
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Taner A. Emear specification estimated by (525				
	(1)	(2)	(3)	(4)	(5)
Regulation, excluding public own. (REGNO)	-0.014 [3.24]***	-0.015 [3.29]***	-0.014 [3.00]***	-0.017 [3.47]***	-0.015 [3.29]***
Percentage with low education		-0.141 [3.11]***	-0.129 [2.73]***	-0.147 [3.06]***	-0.141 [3.10]***
Percentage with intermediate education		-0.065 [1.51]	-0.069 [1.37]	-0.073 [1.64]	-0.064 [1.48]
Percentage females		0.070 [1.82]*	0.068 [1.71]*	0.076 [1.82]*	0.075 [1.90]*
Import-weighted real exchange rate		-0.025 [1.02]	-0.021 [0.82]	-0.025 [1.03]	-0.025 [1.03]
Log worked hours gap		-0.207 [1.94]*	-0.268 [2.42]**	-0.213 [1.81]*	-0.208 [1.94]*
Percentage large firms			0.005		
Age			-0.000		
Employment growth			0.012		
Logarithm of R&D intensity				-0.004 [1.33]	
Union density					0.000 [0.55]
EPL times US job turnover					-0.007 [0.11]
Estimated elasticity of training wrt regulation	-0.472	-0.494	-0.490	-0.500	-0.492
Country by sector dummies	ves	yes	yes	yes	Yes
Country by year dummies	yes	yes	yes	yes	Yes
Sector by year dummies	yes	yes	yes	yes	Yes
Number of observations	1236	1224	1188	1061	1224

	(1)	(2)	(3)	(4)	(5)
Regulation excluding public own (REGNO)	-0.141	-0.161	-0.175	-0.151	-0.167
Regulation, excluding public own. (REGIVO)	[3.84]***	[4.40]***	[4.22]***	[4.25]***	[4.51]***
Percentage with low education		-2.005	-1.938	-2.045	-1.988
		[4.38]***	[4.03]***	[4.38]***	[4.36]***
Percentage with intermediate education		-0.679	-0.646	-0.737	-0.638
		[1.93]*	[1.76]*	[2.12]*	[1.80]*
Percentage females		0.737	0.672	0.643	0.713
C		[1.91]*	$[1./1]^*$	[1.69]*	[1.84]*
Import-weighted real exchange rate		-0.273	-0.203	-0.382	-0.270
		$[1.70]^{\circ}$	2 186	[2.44]	2 2 2 2 0
Log worked hours gap		-2.209	-3.180 [7 70]***	-1.939	-2.229 [2.00]**
		[2.13]	$\begin{bmatrix} 2.79 \end{bmatrix}$	[1.05]	[2.07]
Percentage large firms			[0.66]		
			0.012		
Age			[0.64]		
			0.364		
Employment growth			[0.95]		
Legenthur of D&D interests				-0.069	
Logarithm of R&D intensity				[1.83]*	
Union density					0.001
Onion density					[0.18]
FPL times US job turnover					-1.828
					[1.57]
Estimated alerticity of the initial court of each time.	0.270	0.21(0.245	0.210	0.220
Esumated elasticity of training wrt regulation	-0.279	-0.316	-0.345	-0.319	-0.329
Country by sector dummies	yes	yes	yes	yes	Yes
Country by year dummies	yes	yes	yes	yes	Yes
Sector by year dummies	yes	yes	yes	yes	res

Table 1 (continued). Panel B: GLM specification estimated by QMLE

Number of observations

Notes: Dependent variable: training participation rates. Elasticities are estimated at the sample means computed only for exposed industries. Robust t-or z-values within brackets. *, **, ***: significant at the 10%, 5% and 1% level, respectively.

1236

1224

1188

1061

1224

	(1)	(2)	(2)	(4)	(5)
	(1)	(2)	(3)	(4)	(3)
	0.011	0.011	0.011	0.012	0.011
Barriers to entry and vertical integration (BEVI)	-0.011 [2 10]***	-0.011 [2 17]***	-0.011	-0.015	-0.011 [2 17]***
	[5.10]	[3.17]***	0.128	[3.43]***	0.130
Percentage with low education		[3 08]***	[2 71]***	[3 04]***	[3 07]***
		-0.064	-0.061	-0.073	-0.063
Percentage with intermediate education		[1.49]	[1.36]	[1.63]	[1.45]
		0.069	0.068	0.075	0.069
Percentage females		[1.80]*	[1.70]*	[1.88]*	[1.80]*
Turn and an aighted median changes made		-0.025	-0.021	-0.037	-0.025
Import-weighted real exchange rate		[1.02]	[0.82]	[1.36]	[1.03]
Log worked hours gap		-0.213	-0.271	-0.217	-0.214
Log worked hours gap		[1.99]**	[2.44]**	[1.84]*	[1.99]**
Percentage large firms			0.005		
			[0.29]		
Age			-0.000		
6			[0.12]		
Employment growth			0.013		
			[0.42]	0.003	
Logarithm of R&D intensity				-0.003	
				[1.20]	0.000
Union density					[0.58]
					-0.010
EPL times US job turnover					[0.17]
Estimated elasticity of training wrt regulation	-0.338	-0.351	-0.343	-0.357	-0.350
Country by sector dummies	yes	yes	yes	yes	Yes
Country by year dummies	yes	yes	yes	yes	Yes
Sector by year dummies	yes	yes	yes	yes	Yes
Number of observations	1236	1224	1188	1061	1224

Table 2. Estimates of training as function of BEVI, the index of barriers to entry and verticalintegration.Panel A: Linear specification estimated by OLS

Table 2 (continued).			
Panel B: GLM specification	estimated	by OML	E

	(1)	(2)	(3)	(4)	(5)
					<u> </u>
Barriers to entry and vertical integration (BEVI)	-0.114	-0.129	-0.135	-0.125	-0.134
barriers to entry and vertical integration (DE VI)	[4.16]***	[4.82]***	[4.51]***	[4.68]***	[4.93]***
Percentage with low education		-1.993	-1.919	-2.032	-1.976
recentage with low education		[4.37]***	[4.00]***	[4.47]***	[4.34]***
Percentage with intermediate education		-0.672	-0.638	-0.731	-0.633
		[1.92]*	[1.75]*	[2.11]*	[1.79]*
Percentage females		0.734	0.672	0.650	0.708
č		[1.90]*	[1.70]*	[1.70]*	[1.84]* 0.270
Import-weighted real exchange rate		-0.2/0	-0.259	-0.5/8	-0.2/0
		[1./8] [*]	$[1.0/]^{*}$	[2.45]**	[1./8]* 2.200
Log worked hours gap		-2.42U [2.26]***	-3.32U [2 99]***	-2.084 [1.00]**	-2.390 [2.22]**
		[2.20]	[∠.00]	[1.99]	[2.23]
Percentage large firms			[0.61]		
			0.012		
Age			[0.63]		
			0.388		
Employment growth			[1.01]		
				-0.062	
Logarithm of K&D intensity				[1.62]	
Union domaity					0.000
Union density					[0.01]
EPL times US job turnover					-1.814
					[1.56]
Estimated elasticity of training wrt regulation	-0.218	-0.245	-0.259	-0.251	-0.254
Country by sector dummies	yes	yes	yes	yes	Yes
Country by year dummies	yes	yes	yes	yes	Yes
Sector by year dummies	yes	yes	yes	yes	Yes
Number of observations	1236	1224	1188	1061	1224

Notes: see Table 1.

In the exposed industries the estimated elasticity of training with respect to changes in product market regulation varies with the selected indicator and with the estimation method. Focusing on the indicator REGNO and evaluating elasticities at their sample means in the exposed industries, we find that a 10% decrease in REGNO would increase training incidence by 4.7% to 4.9% percent in the linear model - depending on the specification used - and by 2.8% to 3.4% percent in the GLM specification³⁵. These appears to be economically significant effects, taking into account the fact that regulation indicators slumped by almost 50% in the sample period in the exposed industries.

As discussed above, we can try to capture a bell-shaped relationship between regulation and training by formulating a specification including a quadratic term, where regulation is redefined by adding the 1998 indicator of nation-wide administrative barriers to start-ups to our sector-specific indicators of regulation. However, no significant evidence of a bell-shaped relationship emerges (Table 3). This result might be due to the fact that our indicators are poorly comparable in levels across countries and over time (see data section above). Alternatively, this result can be viewed as consistent with the fact that, for most of our sample, our theoretical model predicts a negative relationship.

Since there are only 15 countries in our sample, we ask whether our results are driven by one specific country. Figure 5 plots the estimates of the parameter of interest, which captures the impact of REGNO on training, obtained by excluding one country at a time for our preferred specification (Table 1, Panel B, Column 2). Estimates appear to be relatively stable and always significant at the 1% level.

	REGNO	REGNO squared / 100
Pasa controls evaluding evaluating rate linear	-0.024	0.085
base controls, excluding exchange rate – intear	[1.47]	[0.63]
Paga controls evoluting evoluting controls CIM	-0.386	2.135
base controls, excluding exchange rate – GLM	[2.44]**	[1.57]
Paga controla linear	-0.023	0.079
Base controls – linear	[1.45]	[0.59]
Pasa controls CLM	-0.382	2.053
Dase controls – OLM	[2.45]**	[1.53]
Paga controls plus exchange rate linear	-0.024	0.081
Base controls plus exchange rate – Intear	[1.48]	[0.60]
Paga controls plus evolutions rate CLM	-0.386	2.083
Dase controls plus exchange rate – OLM	[2.47]**	[1.54]

Table 3. Estimates of training as function of REGNO and its square. Alternative measures

Notes: Dependent variable is the training participation rate. Each row corresponds to a different specification. Base controls are those reported in Columns 2 of Table 1. Robust t- or z-values within brackets. *, **, ***: significant at the 10%, 5% and 1% level, respectively.

³⁵ If E(y|x) = G(z), with z = xb, is the logistic specification, the marginal effect is E(y|x) = G'(z)b.



Figure 5. Sensitivity to country coverage

Note: The figure shows central estimates and confidence intervals obtained by re-estimating the model of Column 2 in Panel B of Table 1 excluding one country at a time.

Next, we check the robustness of our findings to changes in the dependent variable, and report our results in the four rows of Table 4 below. In particular, we replace our measure of training flows with the four alternative measures of training stocks described above. We find that in all cases the negative relationship between training and product market regulation is confirmed by the data. Moreover, the estimated elasticities suggest that a 10 percent reduction of regulation is expected to increase training stocks by 1.2 % to 4.3 %, depending on the selected definition of the stock.³⁶

 $^{^{36}}$ We consider four different measured of the training stock. They are all based on the perpetual inventory method described in section 2 above, but differ with respect to assumption concerning the steady state growth rate. Our preferred measure is computed by assuming that industry-specific steady state growth rates of training stocks are equal to observed mean growth rates of training participation rates in industries where this is positive and 0 elsewhere. As regards alternative measures, in the first, the observed mean growth rates of training participation are used for all industries; in the second, a constant 2% steady state growth rate of training stock is assumed (as assumed by Dearden, Reed and van Reenen, 2006); and in the third, a constant 2.5% steady state growth rate of training stock is assumed, which does not appear to be inconsistent with our data. Using the latter measure, in fact, we cannot reject 2.5% as the average growth rate of the training stock.

	Coefficient	Elasticity
Training steal has magure	-0.062	-0.204
framming stock – base measure	[2.62]***	
Training stock _ alternative measure based on observed growth rates	-0.130	-0.426
raining stock – alternative measure based on observed growth rates	[4.51]***	
Training stock – alternative measure assuming 2% steady state growth	-0.037	-0.122
framing stock – anomative measure assuming 270 steady state growth	[2.15]**	
Training stock – alternative measure assuming 2.5% steady state growth	-0.037	-0.123
framme stock anomative measure assuming 2.570 steady state growth	[2.16]**	

Table 4. Estimates of training stock as a function of REGNO. Alternative measures

Notes: Dependent variable: log of training stocks. Each row corresponds to a different measure. Base measure computed by assuming that industry-specific steady state growth rates of training stocks are equal to observed mean growth rates of training participation rates in industries where this is positive and 0 elsewhere. In row 2, the observed mean growth rates of training participation are used for all industries. In row 3, a constant 2% steady state growth rate of training stock is assumed. In row 4, a constant 2.5% steady state growth rate of training stock is assumed. Elasticities are estimated at the sample means computed only for exposed industries. Robust t-values within brackets. *, **, ***: significant at the 10%, 5% and 1% level, respectively.

As discussed above (see section 2), an alternative to the direct estimation of the relationship between regulation and training is to estimate how training is affected by profitability, measured by the observed Lerner index, and to instrument the latter with a measure of product market regulation. The advantage of this approach is that it allows us to disentangle the effect of regulation on profitability from the effect of profitability on training. The disadvantages are greater measurement errors and the fact that profitability needs to be treated as endogenous in training regressions. Our empirical methodology is instrumental variables in the case of the linear model and the control function approach suggested by Smith and Blundell (1986) in the case of the GLM, using regulatory indicators as instruments. This approach consists of two steps: in the first step, we regress the Lerner index on regulation and other controls; in the second step, we augment specifications including training as the dependent variable and the Lerner index and other controls as explanatory variables with the residual from the first stage regression, and obtain confidence intervals by bootstrapping (see Efron, 1987).

The results from this exercise are presented in the two panels of Table 5 (as above, panel A for the linear model and panel B for the GLM model). As expected, we find that an increase in the Lerner index reduces training incidence and that regulation has a statistically significant positive correlation with the Lerner index (see bottom of the table). In addition, standard tests suggest that the Lerner index is endogenous.³⁷

Depending on the specification of the linear model, a 1% increase in profitability is expected to

reduce training by 1.38% to 1.79% percent, a large effect. These elasticities are smaller but still substantial when we consider the GLM logistic specification. In this case a 1% increase in profitability is associated to a 0.59% to 0.80% reduction of training. Yet, in assessing the economic importance of this effect, one needs to take into account that the cross-country/cross-industry average range of percentage variation of the Lerner index over the sample period is about 7%, while regulatory indicators have varied in our sample by much more (50% on average in treated industries). Interestingly, the estimated compounded effect of a deregulation – that is the derived estimated effect of deregulation on training via the effect of the former on the Lerner index – is very close to the estimate we obtain from reduced form models: a 10% drop in the regulation index is estimated to increase training by 4.4% to 5% in the linear model and by 2.9% to 3.6% in the GLM.

³⁷ In linear models, the Durbin-Wu-Hausman test of endogeneity always reject the null of exogeneity of the Lerner index. In the case of IV estimates obtained using the control function approach, the first-stage residual always attracts a significant coefficient, which provides evidence of endogeneity.

	(1)	(2)	(3)	(4)	(5)
Lerner Index	-1.323	-1.419	-1.391	-1.187	-1.456
	[1.90]*	[2.00]**	[1.82] *	[2.27]**	[1.92]*
Percentage with low education		-0.167	-0.169	-0.176	-0.171
refeelinge with low education		[2.49]**	[2.48]***	[2.71]**	[2.49]**
Percentage with intermediate education		-0.074	-0.071	-0.086	-0.083
		[1.22]	[1.18]	[1.47]	[1.37]
Percentage females		0.142	0.141	0.109	0.144
6		[2.31]**	[2.25]**	[2.10]**	[2.27]**
Import-weighted real exchange rate		-0.001	-0.000	-0.014	0.001
		-0.042	-0.110	-0.042	-0.031
Log worked hours gap		[0.23]	[0.59]	[0.26]	[0.17]
Percentage large firms		2 3	0.040		
r creentage large mins			[1.24]		
Age			0.000		
C			[0.18]		
Employment growth			[0.84]		
Lagorithm of P & D intensity			[]	-0.017	
Logarunni of R&D intensity				[2.11]*	
Union density					-0.002
					[0.96]
EPL times US job turnover					[1 05]
					[1:00]
Durbin-Wu-Hausman exogeneity test $(\gamma^2(1))$	23.75***	24.70***	27.86***	25.89***	27.64***
Coeff. of \mathbf{BECNO} in the first stage regression	0.013	0.013	0.013	0.016	0.013
Coeff. of REGNO in the first-stage regression	[2.67]***	[2.71]***	[2.56]**	[3.20]***	[2.58]***
Elasticity of training to the Lerner Index	-1.613	-1.749	-1.744	-1.381	-1.789
Derivative of training wrt REGNO	-0.017	-0.018	-0.019	-0.019	-0.019
Elasticity of training wrt REGNO	-0.445	-0.486	-0.488	-0.497	-0.488
Country by sector dummies	yes	yes	yes	yes	yes
Country by year dummies	yes	yes	yes	yes	yes
Sector by year dummies	yes	yes	yes	yes	yes
Number of observations	1120	1108	1084	985	1108

Table 5. Estimates of training as function of the Lerner index, instrumented with REGNO. Dependentvariable: training participation rates.Panel A: Linear model, 2SLS

Table 5 (continued). *Estimates of training as function of the Lerner index, instrumented with REGNO. Dependent variable: training participation rates.* Panel B: GLM, Two-step IV estimates

· •	(1)	(2)	(3)	(4)	(5)
Lagged Lerner Index	-11.08**	-12.44**	-13.62*	-9.36**	-13.59**
	[-69.09,-0.05]	[-71.03,-0.87]	[-130.0,0.04]	[-44.74,-0.96]	[-87.96,-1.41]
Residual first stage	11.41*	12.49**	13.64*	9.14**	13.68**
	[-0.48,66.48]	[0.59,69.65]	[-0.56,130.0]	[0.56,38.04]	[1.45,89.30]
Percentage with low education		-2.20*	-2.31*	-2.26**	-2.23*
		[-4.13,0.02]	[-4.93,0.32]	[-4.04,-0.13]	[-4.43,0.45]
Percentage with intermediate education		-0.76	-0.75	-0.85	-0.82
e		[-2.50,1.56]	[-2.60,3.45]	[-2.27,0.84]	[-3.00,1.57]
Percentage females		1.27*	1.31*	0.86	1.29
e		[-0.43,4.02]	[-0.66,6.34]	[-0.48,2.90]	[-0.50,4.85]
Import-weighted real exchange rate		-0.19	-0.01	-0.18	0.02
		[-1.18,1.07] _2 27	-1 31	-0.55	[-1.13,1.37] -0.40
Log worked hours gap		[-5.96.7.05]	[-6.50.15.19]	[-4.70.4.35]	[-6.05.9.22]
Dama anto a a lama firma		[]	0.55	[,]	[
Percentage large lirms			[-1.30,2.35]		
Age			0.02		
1150			[-0.07,0.13]		
Employment growth			0.71		
			[-3.33,3.80]	-0.18*	
Logarithm of R&D intensity				[0 50 0 01]	
T T 1 1				[0.00,0.01]	-0.03*
Union density					[-0.24,0.04]
EDL times US job turneyer					-0.70
EFE times 03 job turnover					[-5.24,13.63]
Coeff of REGNO in the first-stage regression	0.013**	0.013**	0.013**	0.016**	0.013**
	[0.008, 0.017]	[0.008, 0.017]	[0.008, 0.018]	[0.011, 0.021]	[0.008, 0.018]
Elasticity of training to the Lerner Index	-0.651	-0.795	-0.729	-0.589	-0.795
Derived elasticity of training wrt REGNO	-0.289	-0.359	-0.329	-0.317	-0.350
Country by sector dummies	yes	yes	yes	yes	yes
Country by year dummies	yes	yes	yes	yes	yes
Sector by year dummies	yes	yes	yes	yes	yes
Number of observations	1120	1108	1084	985	1108

Notes: Dependent variable: training participation rates. Elasticities with respect to the Lerner index are estimated at the global sample mean; elasticities with respect to regulation, excluding public ownership (REGNO), are estimated at sample means computed only for exposed industries. Robust t-values within brackets in Panel A. Bias-corrected bootstrapped confidence intervals at the 5% statistical level, obtained with 1000 replications, within brackets in Panel B. In Panel A: *, ** and *** means significant at the 10%, 5% and 1% level, respectively. In Panel B, * and *** means that the bias-corrected bootstrapped confidence interval at the 10% and 5% confidence level, respectively, does not include 0.

Conclusions

Does product market deregulation affect workplace training, and if yes, in what direction? This paper has addressed this question from both the theoretical and empirical viewpoint. Our theory suggests that a relationship between deregulation and training exists, but that its sign is ambiguous. On the one hand, a reduction in the barriers to entry for a given number of firms compresses profits per unit of output, and thereby reduces training. On the other hand, and conditional on profits per unit of output, additional entry increases the output gains from training, which facilitates investment. These output gains occur because additional training reduces the relative product price and the sensitivity of product demand to prices is larger, the greater the degree of competition in the product market.

Our numerical simulations show that - for reasonable values of the parameters - a positive relationship between deregulation and training prevails. Our empirical analysis, based on repeated cross section data extracted the European Labour Force Survey, examines the evidence for a sample of 15 European countries and 12 industrial sectors, which we follow for about 8 years. Our results are unambiguous and show that an increase in product market deregulation generates a sizeable increase in training incidence. These findings highlight that an important link in the relationship between deregulation and productivity growth is the investment in human capital which takes place in firms – or workplace training.

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Appendix

A. The bargaining model when both skilled and unskilled workers bargain over wages and employment.

In the text we have assumed that unskilled labour does not actively participate to the bargain. In a more general setting, let unskilled and skilled labour differ in the relative bargaining power, δ for the unskilled and β for the skilled, with $\beta > \delta$. Furthermore assume that in the event of failure to settle both types of workers separate from the firm and earn the reservation wage, while the firm makes zero profits, and assume that the bargaining solution is obtained by maximizing the following expression

$$\beta \ln \left[(W_{si} - V)T_i L_i \right] + \delta \ln \left[(W_{ui} - V)(1 - T_i) L_i \right] (1 - \beta) \ln \left\{ P_i Y_i - L_i (W_{si} T_i + W_{ui}(1 - T_i)) \right\}$$
[A.1]

Where W_s and W_u are the wages earned by skilled and unskilled labour in the event of settlement. Then we can show that wages and prices are given by

$$T_i W_{si} = \beta P_i \frac{Y_i}{L_i} + V(T_i - \beta)$$
[A.2]

$$(1 - T_i)W_{ui} = \delta P_i \frac{Y_i}{L_i} + V(1 - \delta - T_i)$$
[A.3]

$$P_i A[1 + (\gamma - 1)T_i] = \frac{\theta}{\theta - 1}V$$
[A.4]

While condition [15] in the text still holds, condition [14] needs to be modified as follows

$$\pi = \frac{1 - \beta - \delta}{\theta} - \frac{\mu T^2}{2A[1 + (\gamma - 1)T]} = \rho$$
[A.5]

And the analysis in the text still goes through.

B. The right-to-manage model

A popular alternative to the efficient bargain model is the right to manage model, which allocates to the employer the exclusive right to select employment after the parties have bargained over wages. In this Appendix we briefly sketch the equilibrium with right to manage. Further details are available from the authors upon request.

Since employment is set after the bargain, we start from profit maximization net of the training costs, which are sunk. This yields

$$P_i(1 - \frac{1}{\theta})A[1 + (\gamma - 1)T] = W_iT_i + V(1 - T_i)$$
[A.6]

Using this in the Nash maximand [4] and maximizing the outcome with respect to prices, we obtain

$$P_{i} = \frac{\theta + \beta - 1}{\left(\theta - 1\right)^{2}} \theta \frac{V}{A\left[1 + \left(\gamma - 1\right)T\right]}$$
[A.7]

Replacing [A.6] and [A.7] into ex-ante profits, optimal training is given by

$$(\theta - 1)(\gamma - 1)\left[\frac{V(\theta + \beta - 1)}{(\theta - 1)^2} - \frac{\mu T_i^2}{2}\right] = \mu T_i [1 + (\gamma - 1)T_i]$$
[A.8]

We add to [A.8] two additional equations, one for the determination of V in general equilibrium and another for the entry condition

$$V = \frac{(\theta - 1)^2}{\theta(\theta + \beta - 1)} A [1 + (\gamma - 1)T]$$
[A.9]

$$\Pi = \frac{1}{\theta} - \frac{\mu T^2}{2A[1 + (\gamma - 1)T]} = \rho$$
[A.10]

This system of three equations in three unknowns can be further simplified to yield

$$\mu T = (\theta - 1)(\gamma - 1)\rho A$$
[A.11]
$$\sigma g(m) = \frac{1}{\rho + \frac{\mu T^2}{2A(1 + (\gamma - 1)T))}}$$
[A.12]

Inspection suggests that [A.11] is equal to equation [15] and that [A.12] only differs in the numerator on the right hand side. It follows our main Proposition still holds, but that the relevant condition becomes:

$$\rho > \frac{1}{\theta(\rho)} \frac{\theta(\rho) - 1}{\theta(\rho)}$$
[A.13]

C. The equilibrium when the cost of entry is fixed

Assume that the cost of entry C is fixed, rather than proportional to output. The two equilibrium conditions become

$$\mu T = (\theta - 1)(\gamma - 1)C\frac{m}{\gamma}A$$
[A.14]

$$\pi = \frac{1 - \beta}{\theta} - \frac{\mu T^2}{2A[1 + (\gamma - 1)T]} = C\frac{m}{Y}$$
[A.15]

We show here that the proposition in the text still holds: total differentiation of [A.14] and [A.15] yields

$$\Sigma_1 dm + \Sigma_2 dT = \Sigma_5 dC$$

$$\Sigma_3 dm + \Sigma_4 dT = \Sigma_6 dC$$

where

$$\begin{split} \Sigma_{1} &= \sigma g'(m)(\gamma - 1)m \frac{C}{Y}A + (\sigma g(m) - 1)(\gamma - 1)\frac{C}{Y}A \qquad \Sigma_{2} = -\mu \qquad \Sigma_{3} = -\frac{1 - \beta}{\sigma g(m)^{2}}g'(m) - \frac{C}{Y}\\ \Sigma_{4} &= -\frac{2\mu T + \mu T^{2}(\gamma - 1)}{2A[1 + (\gamma - 1)T]^{2}} \qquad \Sigma_{5} = -(\sigma g(m) - 1)(\gamma - 1)\frac{m}{Y}A \qquad \Sigma_{6} = \frac{m}{Y} \end{split}$$

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Since the determinant of the Jacobian is negative when $\theta < +\infty$ and C > 0, $\frac{dT}{dC} < 0$ if $\Sigma_1 \Sigma_6 - \Sigma_3 \Sigma_5 > 0$, that is if

$$\frac{1-\beta}{\theta(C)}\frac{\theta(C)-1}{\theta(C)}\frac{Y}{m} < C \le \frac{1-\beta}{\theta(C)}\frac{Y}{m}$$
[A.16]

Taking into account that $\rho = C \frac{m}{Y}$, eq. [A.16] is equivalent to [16].

We ask now whether, for a given configuration of parameters, deregulation is more likely to increase training when barriers to entry are a fixed costs or when they are proportional to output. First, note that $\max\{C\} = (1 - \beta)Y$ and $\max\{\rho\} = 1 - \beta$. To make things comparable, with no loss of generality, we can assume Y = 1, which is equivalent to express C as a percentage of the size of the market, so that $\max\{\rho\} = \max\{C\}$. Then define $\hat{\rho} = \sup I_{\rho}$ and $C = \sup I_{C}$, where $I_{\rho} = \{\rho : \frac{\partial T}{\partial \rho} > 0\}$ and $I_{C} = \{C : \frac{\partial T}{\partial C} > 0\}$. From [A.11], we have that $\hat{\rho} / \max\{\rho\} = m(C)C / \max\{C\} > C / \max\{C\}$. In other words, when entry costs are fixed deregulation will start reduce training for a smaller value of entry costs relative to their maximum possible value, than in the case when entry costs are proportional to output. If we think in terms of Figure 2, in relative terms, the summit of the bell is even more on the left if fixed entry costs C are on the x-axis.

D. Equilibrium manifold when training incidence is measured using training stocks

Figure A1 replicates Figure 4 by imposing that for $\rho = 0.31$ optimal training incidence be equal the median training stock (38,9%), using our preferred measure of training stock. Although *T* can be very large, Figure A1 also shows that for the selected configuration of the parameters equilibrium training incidence is also less than 1, as one would expect given that the two conditions in the Lemma are always satisfied.



Figure A1: The relationship between ρ , γ and T with β =0.5 and μ such that median training rates correspond to median regulation levels

E. Definition of raw variables, sources and descriptive statistics

Data from the OECD Database on Training

All variables refer to employees aged between 25 and 54 years working at least 30 hours per week and with at least one month of tenure. Data are derived from Eurostat, European Labour Force Surveys.

Training participation rate

Definition: Share of employees that took training in the 4 weeks preceding the survey.

Share of males

Definition: ratio of men employees to total wage and salary employment.

Average age

Definition: average age of employees. Data are available by 5-year classes in the micro-data. Data are aggregated assuming that each individual's age corresponds to the average of each class.

Share low education

Definition: Share of employees with educational attainment corresponding to ISCED 1-3.

Share medium education

Definition: Share of employees with educational attainment corresponding to ISCED 4.

Share firms with more than 50 employees

Definition: Ratio of the number employees of firms with more than 50 employees to total wage and salary employment. Since in the micro-data respondents may simply say that firm size is greater than 10 employees, with no distinction between more or less than 50 employees, the share is obtained as the product of the ratio of the number of employees in firms with more than 50 employees to the number of employees in firms with more than 10 employees to the number of employees in firms with more than 10 employees to total wage and salary employment.

Data on product market regulation

All indicators vary from 0 to 6 from least to most restrictive. They are drawn from the OECD Regulatory Database.

Indicators of sector-specific product market regulation

Definition: Indicators of entry barriers, public ownership, market share of the dominant player(s), vertical integration in network industries and price controls. They cover seven industries (electricity, gas, rail, road freight, air transport, post and telecommunications).

Administrative barriers on start-ups

Definition: Aggregate indicators concerning administrative barriers for start-ups, including administrative opacity, that apply to all sectors in the economy. The indicator is net of sector-specific regulatory barriers. Data refer to 1998

Other data

Employment

Definition: total persons engaged. Source: Groningen Growth and Development Centre 60-Industry Database.

Hours worked

Definition: average hours worked per persons engaged. Source: Groningen Growth and Development Centre 60-Industry Database.

Import weighted real exchange rate

Definition:

$$x_{ikt} = \sum_{i=1}^{I} \sum_{l=1}^{L} m_{iklt_0} e_{klt} p_{lt} / p_{kt}$$

where x stands for the import-weighted real exchange rate, m is to the import share from country l in industry i of country k at a fixed time period t_0 (early 1980s in these data) - the import weights thus vary across industries and countries but are constant in time - e is to the nominal bilateral exchange rate between countries k and l at time t - which varies across partner countries and time, but not across industries - the p variables refer to price levels, as approximated by the GDP deflator, in countries l and k respectively. Within a country in a given year, the variation in industry-specific real exchange rates derives entirely from differences in the import pattern across industries. An increase in the industry-specific exchange rate represents a real depreciation in the price of output produced in industry i of country k relative to its trading partners (weighted by import shares). Put differently, an increase in the industry-specific exchange rate represents an improvement in the terms of trade in industry i for country k. Source: OECD (2007).

R&D intensity

Definition: ratio of Business Enterprise Expenditures in R&D to value added. Source: OECD STAN, ANBERD and R&D Databases.

Observed Lerner index

Definition:

$$L_{ijt} = \frac{Y_{ijt} - CV_{ijt}}{Y_{ijt}}$$

where L is the observed Lerner index in country i, industry j and time t, CV are variable costs in nominal terms and Y is the value of output (see e.g. Klette, 1999). In practice, CV is the sum of intermediate inputs costs, labour costs and estimated cost of capital. Capital stock is constructed by perpetual inventory method for countries where it is not provided in national accounts at a sufficiently disaggregated level. However, since reconstructed capital stocks are available only in volume terms, in practice nominal capital stocks are obtained by dividing them by value added in volume terms and pre-multiplying them by nominal value added. In the calculation of the cost of capital, we follow Griffith et al. (2006) and assume that capital flows freely across borders so that all countries face a world interest rate, for which we use the US long-term interest rate.

Index of Employment Protection Legislation

Definition: OECD aggregate summary indicator of the stringency of employment protection legislation incorporating both regular contracts and temporary work. Source: OECD, Employment Outlook 2004.

Union density

Definition: Share of workers affiliated to a trade union (in %). Disaggregated data are available only for two macro-sectors Transport and Industry (Manufacturing plus Energy) in Austria, Germany, Italy, the Netherlands, Norway, Spain and Sweden. The macro-sector average is assigned to all subsectors. For the other countries, the same value is assigned to all sectors. Source: Ebbinghaus and Visser (2000).

Job creation and destruction rates

Definition: US average gross job creation and destruction rates aggregated from establishment level data (assuming, for continuous firms, that net employment changes are equal to gross employment changes). Data refer to 1990-1996. Source: Haltiwanger, Scarpetta and Schweiger (2006).

List of countries

Austria, Belgium, Germany, Denmark, Spain, Finland, France, UK, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, and Sweden.

Table AT. Lis	t of industries.
NACE Rev. 1	Description
15-16	Food products, beverages and tobacco manufacturing
17-19	Textiles, textile products, leather and footwear manufacturing
20	Wood and wood products manufacturing
21-22	Pulp, paper and related products manufacturing, printing and publishing
23-25	Chemical and fuel products manufacturing, rubber and plastics
26	Other non-metallic mineral products manufacturing
27-28	Basic metals and fabricated metal products manufacturing
34-35	Transport equipment manufacturing
29-33	Other machinery and equipment manufacturing
40-41	Electricity, gas and water supply
60+62	Land and air transport
64	Communications services

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Table A2. Descriptive statistics.

Variable	Observations	Mean	Standard deviation
Training participation rate	1236	0.078	0.075
Training stock	1236	0.476	0.457
REGNO	1236	0.820	1.593
BEVI	1236	0.790	1.584
Share males	1236	0.756	0.143
Average age	1236	38.86	1.465
Share firms with > 50 employees	1200	0.561	0.223
Share low education	1224	0.373	0.209
Share medium education	1224	0.463	0.177
Import weighted real exchange rate	1236	1.297	1.914
Hours gap	1236	0.002	0.012
Employment growth	1236	-0.002	0.037
Union density	1236	44.526	24.69
EPL*TURN	1236	0.411	0.168
Lerner index	1120	0.100	0.062