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Employment effects of on-the-job human capital acquisition∗†

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Abstract

This paper quantifies the combined effect on-the-job training and workers’ on-the-job learning decisions have on aggregate employment. Initially, we present an index of on-the-job human capital acquisition based on data from the OECD program for international assessment of adult competencies. The data shows a positive relationship between the on-the-job training and on-the-job learning indexes and a strong positive correlation between the human capital index and employment rates across OECD economies. Next, with the on-the-job human capital acquisition we build a search and matching model that hinges on the training provided by firms as well as workers’ learning. The model also includes education along with taxes that increase and decrease human capital investments. We calibrate the model to the average OECD economy and find that education and taxes account for more than half of the differences in human capital acquired on the job and employment. Moreover, one fifth of the effect education and taxes have on employment is due to human capital acquisition. Finally, we analyze subsidies to training costs and conclude that a 10% reduction in marginal training cost increases long-term employment by 0.5 percentage points.

JEL Classifications: E24, J24, J64.

Keywords: Employment, labor productivity, human capital, search and matching

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1 Introduction

In recent decades, the skills the workforce requires have become increasingly more demanding, with business and employees alike having to adapt to more increasingly complex technologies (see, OECD, 2006, 2010a, 2011). In this regard, participating in job training activities and learning on the job have gained importance, since these activities enable workers to update their competencies and acquire new skills which are, more often than not, compensated in the labor market (see, OECD, 2010b, 2013). In addition to the positive effects these activities have on productivity, they also make the workplace more attractive for workers, increase their motivation, participation and, consequently, boost the employment rate (OECD, 2004; Grip, 2008). Even though the relevance for policy-makers to have empirical evidence concerning such issues, there have been very few papers published that have studied the economic impact that informal learning process has in the workplace. Most papers, following seminal studies in human capital theory (e.g., Arrow, 1962; Mincer, 1962), focus on experience as a proxy of learning in the workplace. These studies show that work experience (as a proxy of learning in the workplace and learning by doing) has been a key determinant of workers’ economic outcomes.

In this paper we explore the role human capital and, in particular, on-the-job human capital acquisition (formally and informally) have in explaining differences in employment rates across OECD economies. We use data from the OECD Program for the International Assessment of Adult Competencies (PIAAC) that, through a number of questions, allows us to identify formal and informal learning in the workplace in OECD countries.

First, using the PIAAC database, we construct an index of on-the-job human capital acquisition (OJHCA). This index combines two other indexes, namely an on-the-job training index and another that measures learning in the workplace. The former comprises formal on-the-job training sessions or training activities, while the latter includes the learning of new work-related competencies gained through the interaction between co-workers and supervisors (informal learning) and from the tasks workers perform on their own (i.e. learning-by-doing).

Second, in the spirit of Mortensen and Pissarides (1994), we build an augmented search and matching model with on-the-job human capital acquisition that depends on both on-the-job training and learning. As search and matching models are workhorses for analyzing the labor markets, these models are suitable for our objective because, as shown by Acemoglu and Pischke (1999a,b), companies find it optimal to offer general training to workers in the presence of frictions in the labor market, contrasting with Becker (1964) results in a perfect labor market set-up. The idea is that firms make higher profits from trained workers because their wage increases are less than the associated productivity increase. In our model, workers acquire skills in an initial stage and either become fully-trained employees or are dismissed. Acquiring skills is costly for both the firm and the worker because the firm spends resources
on training workers and the worker makes an effort to learn. Moreover, training activities encourage workers to increase their learning in the workplace because the resulting increase in their wages will offset the costs of learning and part of the cost transferred to them from their respective companies. In the case of a fully-trained worker losing their job, their skills are general and transferable to other firms. That said, they may need to acquire new skills in their new job.

The model also incorporates payroll taxes and education as factors that affect, among others, human capital investment. On the one hand, payroll taxes are negatively correlated with employment rates and the human capital acquisition index. In our model, not only do taxes increase employment opportunity costs (e.g. Prescott, 2004) but they also increase the implicit marginal cost of learning as a result of reducing the net wages received by workers. Consequently, the worker’s incentive to learn on-the-job drops and, due to its complementarity, so too does the level of training provided by the firm. On the other hand, formal education increases labor productivity, which increases the net returns of training investments made by firms and reduces the workers effort to learn. Education reduces the implicit marginal costs of training and learning, which is in line with the observed complementarity between on-the-job training and formal education found in previous studies (see, e.g. Cairó and Cajner, 2018).

Third, to quantify the effect on-the-job human capital acquisition has on employment, we calibrate the model using the OECD average as our benchmark economy. Then, we decompose the effects education and payroll taxes have to account for the differences in on-the-job human capital acquisition, productivity and employment. The model with exogenous variation in education and payroll taxes accounts for 52% of the observed gap between countries in the highest and the lowest tertiles of the OJHCA, and 80% of the employment gap between these two groups of countries. Our numerical exercise reveals that education accounts for 61% of the differences, while payroll taxes accounts for the remaining 39%. Moreover, between 21% to 25% of the effect education and payroll taxes have on employment is due to the differences in the investments made in human capital on the job. Our model also predicts that cutting taxes or increasing the share of tertiary-educated individuals by 1 percentage point (p.p.) will increase the employment rate by 0.24 and 0.57 p.p., respectively. In a subsequent exercise, we allow countries to differ in terms of their marginal costs of training and learning; specifically, we simulate the observed cross-country differences in the OJHCA index by adjusting the marginal costs of training and learning and compare the model’s predictions for the employment rate with actual data. That is, on top of education and payroll taxes, we take the country-specific policies that determine the levels of training and learning as given. In general, the model performs well in explaining the positive association observed between human capital and employment rates. The model is able to reproduce the differences in employment rates between the groups of countries in the highest and lowest tertiles of the OJHCA distribution and, furthermore, the difference between the model’s predictions and the
actual values of employment is less than 5 p.p. in 20 out of 25 OECD countries.

Finally, since the model is able to reproduce the relationships between education, payroll taxes, OJHCA and employment, we analyze a public policy that consists of a subsidy to marginal training costs in an aim to increase human capital and employment. The subsidy not only encourages training, but also encourages workers to learn in the workplace, thus further increasing their on-the-job acquired human capital. We find that a 10% cut in marginal costs of training increases employment by 0.5 p.p.

This paper has obvious parallels with studies documenting a positive association between on-the-job training and employment. In a broader ranging report, the OECD (OECD, 2004) presents evidence of a positive relationship between job training participation and aggregate employment rates after controlling for formal education, GDP growth and labor market institutions. In line with this hypothesis, Figure 1(a) presents the raw correlation between on-the-job training and the employment rate for OECD countries.1 Specifically, it shows that on-the-job training has a strong positive correlation with employment ($R^2 = 0.57$ in the OLS regression).

Beyond formal training, some scholars have focused on the role of workplace learning. Barron et al. (1997) show the importance of these learning processes in the U.S. Specifically, these authors document that, during the first quarter following the hiring of a new worker, more than one-third of training (54.5 hours) is provided through a so-called ‘learning by watching co-workers’ process, while the other two-thirds correspond mainly to formal sessions of on-the-job training or training activities provided by supervisors and co-workers. In the same vein, Bishop (1996) finds that learning-by-doing plays an important role in the increase in employee productivity during the first two years of job tenure in a firm. Thus, learning through experience and learning from co-workers and supervisors would appear to capture the essence of on-the-job learning.

More recently, several studies stressed that workers are continuously learning in the workplace (i.e., learning from co-workers and supervisors and learning-by-doing) and that has a positive effect on productivity and, subsequently, on economic performance (e.g. Grip, 2008; Destré et al., 2008; De Grijt, 2015; Ferreira et al., 2017, 2018). Moreover, Ferreira et al. (2017) document empirical evidence of complementarity between on-the-job training and on-the-job learning for both temporary and permanent employees in OECD countries. This positive association between on-the-job training and learning can be seen from our data. We present this raw correlation in Figure 1(b).2 Taking this one step further, Figure 1(c) shows that the relation between human capital acquired on-the-job and the employment rate is strengthened

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1Drawing its data from PIAAC, the training variable measures the proportion of workers receiving on-the-job training over the last 12 months.

2The learning index corresponds to the percentage of individuals involved in learning-by-doing and learning from co-workers or supervisors at least once a week.
when we combine training and learning activities as a measure of on-the-job human capital acquisition. Notice that the $R^2$ from the linear regression between on-the-job human capital and employment is 0.66, which is higher than the 0.57 obtained when we regress on-the-job training and employment in Figure 1(a).

Our paper contributes to this literature since, to the best of our knowledge, this is the first paper that use a search and matching model to study the duel effects on-the-job training and workers’ on-the-job learning decisions have on employment rates across OECD economies. Thus, we believe that our model is a good instrument to improve the understanding of how the different components (training and learning) of on-the-job human capital acquisition affect labor markets.

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3Section 2 describes on-the-job training, learning and human capital indexes in greater detail.

4The positive relationship between employment and the OJHCA remains significant even after controlling for the share of workers with tertiary education as a proxy of the level of formal education.
The remainder of this paper is organized as follows. In section 2 we describe our on-the-job training, learning and human capital acquisition indexes. Section 3 presents the model and Section 4 contains the calibration and main quantitative exercises. Finally, section 5 draws the conclusions.

2 On-the-job human capital acquisition index

In this section, we construct an On-the-Job Human Capital Acquisition index, based on data drawn from the PIAAC. The aim of this index is to capture both formal and informal learning in the workplace. As a measure of formal learning, the index includes information about worker participation in formal training programs provided by employers. In the case of informal learning, the index incorporates both worker interaction with co-workers and supervisors and, the acquisition of skills through learning-by-doing.

The PIAAC developed and conducted the Survey of Adult Skills. This survey assesses adult (16-65-year-olds) proficiency in three key information-processing skills: literacy, numeracy and problem solving in technology-rich environments. The survey has been performed in 33 OECD countries (in two rounds: the first from August 2011 to March 2012 in 24 countries and the second from April 2014 to March 2015 in 9 countries). Among others, the PIAAC survey measures skills in the workplace, specifically, the relevance of on-the-job training and learning in the workplace (from co-workers/supervisors and from the worker’s own experience).5

We use three variables from the PIAAC survey to build our On-the-Job Human Capital Acquisition Index. First, we use the on-the-job training variable (OJT) which measures whether the worker claims to have attended (or not) formal training sessions organized in the workplace or provided by their supervisors or colleagues over the preceding 12 months. Second, using two qualitative variables, we build an on-the-job learning index (OJL). Specifically, we consider: i) how often workers declare themselves as having learned new work-related competencies from co-workers or supervisors (learning from co-workers) and, ii) how often their jobs involve learning-by-doing from the tasks that they perform (i.e. learning-by-doing). In all three cases, we normalize these indexes by considering the different scales of the raw data before integrating them into the OJHCA index.6

On-the-job training index

The OJT index measures just how widespread formal training activities are on a country level (extensive margin). Specifically, in building this index, we draw on responses to the following

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5For details see, http://www.oecd.org/skills/piaac/

6Owing to problems of data availability in relation to some of the variables we use in the analysis, we had to exclude five countries from our sample. Thus, our final sample is made up of 28 of the 33 OECD countries surveyed.
question in the PIAAC survey:

“During the last 12 months, have you attended any organised sessions for on-the-job training or training by supervisors or co-workers?”

Given that the answer to this question is either “yes” or “no”, we can compute the OJT index as the percentage of individuals who have received on-the-job training in the last 12 months:

\[
\text{Index OJT} = \frac{\text{yes}}{\text{total}} \times 100.
\]

Figure 2(a) presents the histogram for the OJT index. As can be seen, the index shows a sizable variation across the countries. More specifically, the index ranges from countries in which less than 10 percent of workers reported having participated in formal on-the-job training sessions in the preceding year to countries in which formal training sessions involve more than 40 percent of employees (see Table 4 in the appendix).

**On-the-job learning index**

In building this index, we draw on responses to a further two PIAAC questions:

1. “In your own job, how often do you learn new work-related things from co-workers or supervisors?”
2. “How often does your job involve learning-by-doing from the tasks you perform?”

The possible answers to both questions are as follows: Never; Less than once a month; Less than once a week but at least once a month; At least once a week but not every day; Every day. Then, we compute the two indexes as the percentage of individuals participating in these activities at least once a week.

\[
\text{Index learning from coworkers} = \frac{\text{more than once a week}}{\text{total}} \times 100,
\]

\[
\text{Index learning by doing} = \frac{\text{more than once a week}}{\text{total}} \times 100.
\]
These partial indexes are then integrated to compute the OJL index as the geometric mean.

\[ \text{Index OJL} = \sqrt{\text{Index learning from coworkers} \times \text{Index learning by doing}}. \]

Figure 2(b) presents the histogram for the OJL index. As with the training index, the OJL index shows substantial variation across countries, ranging from almost 20 to nearly 70 percent (see Table 4 in the appendix).

**On-the-job human capital acquisition**

Finally, we integrate the training and learning indexes (OJT and OJL) to compute the OJHCA index by taking the geometric mean of these two indexes.
\[ \text{Index } OJHCA = \sqrt{\text{Index } OJT \times \text{Index } OJL}. \] (1)

Figure 2(c) shows that the OJHCA index varies considerably across the OECD countries, reflecting the high degree of dispersion in both of its components (the OJT and OJL indexes).

3 The model

The economy consists of a continuum of measure one of risk-neutral, infinitely-lived workers and risk-neutral, infinitely-lived firms. Workers and firms discount future payoffs at a common rate \( r \) and capital markets are perfect. Time is continuous. There are employed and non-employed (unemployed) workers making up the working age population.\(^7\) All workers have an exogenous level \( \epsilon \) of formal education, which is complementary to the level of human capital acquired on the job (see Cairó and Cajner, 2018). Moreover, some employed workers are fully trained workers who have already acquired the general level of on-the-job human capital \( h \), while others are newly-employed workers involved in the training and learning process. These newly-hired workers become fully trained at the constant rate \( \iota \), where the inverse of \( \iota \) captures the average duration of training process. On the other hand, the variable \( h \) contains both the on-the-job training \( \xi \) per matched worker and the level of on-the-job learning \( l \). The former corresponds to organized sessions for on-the-job training or training activities by supervisors and/or co-workers and is decided by the firm, while the latter is decided by the worker and includes their learning of new work-related things through the interaction with co-workers and supervisors and from the tasks they perform on their own. Only fully-trained workers keep their level of human capital when losing their jobs. However, these unemployed workers can lose their skills acquired on the job at the constant rate \( \delta \). Similar to Pissarides (1992) and Ljungqvist and Sargent (1998), workers face losses of human capital when unemployed.

3.1 Job and worker value functions

There is a time-consuming and costly process of matching unemployed workers and job vacancies, which is captured by a standard constant-return-to-scale matching function

\[ m(u, v) = m_o u^\alpha v^{1-\alpha}, \] (2)

\(^7\)For simplicity, we put together both unemployed and inactive workers. This assumption is not unrealistic since many OECD countries show high flows between employment and inactivity. For example, according to the Eurostat labour market flow statistics, 52% of ins to employment and 60% of outs from employment are from/to inactivity. In turn, and according to the Bureau of Labor Statistics, the flows between employment and inactivity represent more than 70% of the total flows to/from employment in the U.S.
where \( m_o \) and \( \alpha \) are the matching function parameters, \( u \) is the number of unemployed, and \( v \) the number of vacancies. Among the unemployed are workers \( u_i \) whose skills acquired in previous jobs are portable to other jobs and are workers \( u_e \) who do not have acquired portable skills or the skills became obsolete, thus \( u = u_i + u_e \). However, all unemployed workers compete for the same jobs. Hence, the aggregate rates at which unemployed workers find jobs, \( f(\theta) = m(u, v) / u \), and vacancies are filled, \( q(\theta) = m(u, v) / v \), both depend on the vacancy-unemployment ratio \( \theta \) (labor market tightness). Note as well that \( f(\theta) = \theta q(\theta) \), \( f'(\theta) > 0 \), and \( q'(\theta) < 0 \).

Vacancies may either be filled or not. If the position is not filled, the firm incurs a flow cost \( c \). A vacancy is filled at the endogenous rate \( q(\theta) \), and with probability \( \lambda_k = u_k / u \), the position is filled with a worker of type \( k = e, i \), yielding a positive value \( J_k - V \) during job creation. The value functions \( J_k \) and \( V \) stand for the value that the firm attributes to a filled and vacant position, respectively.

Each firm has constant returns to scale production technology with labor as the sole production factor. Filled positions can be destroyed at a constant hazard rate \( s \). The firm’s output per worker \( y \) depends on the level of education, the human capital acquired on the job and a scale parameter \( A \), that captures the determinants of labor productivity other than those related to the total level of human capital. We also assume decreasing returns to the level of on-the-job human capital \( h \), which is the geometric mean of training \( \xi \) and learning \( l \). Specifically, we assume that a filled job produces \( y = A e^\psi (\xi l)'^\phi \) with \( \phi, \psi \in (0, 1) \). In turn, firms pay wages \( w_k \), payroll taxes \( \tau \) and incur linear training costs \( \mu \xi \) during the training process of newly-hired workers, where \( \mu \geq 0 \) is the marginal cost of training. In contrast, job positions with fully-trained workers do not incur training costs. The values \( V \) and \( J_k \) are given by the following expressions:

\[
\begin{align*}
  rV &= -c + q(\theta) [\lambda_i(J_i - V) + \lambda_e(J_e - V)] , \\
  rJ_e &= Ae^\psi h^\phi - (1 + \tau)w_e - \mu \xi + \nu(J_i - J_e) - s(J_e - V) , \\
  rJ_i &= Ae^\psi h^\phi - (1 + \tau)w_i - s(J_i - V).
\end{align*}
\]

Unemployed individuals receive an unemployment benefit \( b \) and, at rate \( f(\theta) \), find a job that yields net value \( W_k - U_k \), where \( W_k \) and \( U_k \) stand for the value that the worker attributes to employment and unemployment, respectively. Employed workers earn the endogenous wage \( w_k \) and newly-hired workers receiving on-the-job training also incur on-the-job learning with flow costs \( \sigma l \). These learning costs can be related, for example, to the leisure forgone when the worker allocates part of their daily rest or breaktime at work to improve their job related skills. The values associated with different worker status – unemployed and employed – are
given by the following expressions:

\[ rU_e = b + f(\theta)(W_e - U_e), \]  
(6)

\[ rU_i = b + f(\theta)(W_i - U_i) - \delta(U_i - U_e), \]  
(7)

\[ rW_e = w_e - \sigma l + \iota(W_i - W_e) - s(W_e - U_e), \]  
(8)

\[ rW_i = w_i - s(W_i - U_i). \]  
(9)

We also include a free entry condition for vacancies. Hence, we assume that firms open up vacancies until the expected value of doing so becomes zero, that is

\[ V = 0. \]  
(10)

### 3.2 Wage determination

We assume wages to be the result of bilateral Nash bargaining between workers and employers. The solution is the wage that maximizes the weighted product of the worker’s and the firm’s net return from the job match. The first-order conditions yield the following equations:

\[ (1 - \beta)(1 + \tau)(W_k - U_k) = \beta J_k, \quad \text{for} \quad k = e, i, \]  
(11)

where \( \beta \) and \( 1 - \beta \) represent the bargaining power of the worker and the firm, respectively.

We define the surplus \( S_k \) resulting from the match to be \( J_k + (1 + \tau)(W_k - U_k) \). To divide this surplus between the firm and the worker, Nash bargaining implies that workers obtain a fraction \( \beta/(1 + \tau) \) of the total surplus generated from the match (the tax reduces the value of a job for the worker) and firms receive a fraction \( 1 - \beta \), i.e. \( (1 + \tau)(W_k - U_k) = \beta S_k \) and \( J_k - V_k = (1 - \beta)S_k \).

### 3.3 Stationary equilibrium

#### Dynamics of employment

We normalize the labor force to one and consider the fact that individuals are either employed \( (n) \) or unemployed \( (u) \). There are unemployed workers with portable skills \( (u_i) \) and without \( (u_e) \), and employees who are fully trained \( (n_i) \) and new entrants \( (n_e) \),

\[ n + u = 1, \]  
(12)

\[ u_i + u_e = u, \]  
(13)
\[ n_i + n_e = n. \] (14)

Then, using (12)-(14) and given the state-contingent ratio of vacancies to unemployment \( \theta \), employment \( n_k \) and unemployment \( u_k \) evolve according to the following backward-looking differential equations:

\[ \dot{n}_e = f(\theta)u_e - (\iota + s)n_e, \] (15)
\[ \dot{n}_i = f(\theta)u_i + \iota n_e - s n_i, \] (16)
\[ \dot{u}_i = s n_i - (\delta + f(\theta))u_i, \] (17)
\[ \dot{u}_e = s n_e - f(\theta)u_e. \] (18)

At equilibrium, \( \dot{n}_k = \dot{u}_k = 0 \) for \( k = e,i \). Thus, we obtain the equilibrium employment rate

\[ n = \frac{f(\theta)}{s + f(\theta)}. \] (19)

**Surplus**

Using equations (5), (6), (7), (9), and (11) we obtain the surplus resulting from the match of an incumbent worker to a job position,\(^8\)

\[ S_i = \frac{Ae^\psi h^\phi - (1 + \tau)b - \frac{\delta}{r+\delta} f(\theta)S_e}{r + s + \frac{\beta f(\theta)}{r+\delta}}. \] (20)

Similarly, using equations (4), (6), (7), (8), and (11), we obtain the surplus resulting from the match of an entrant worker to a job position,

\[ S_e = \frac{Ae^\psi h^\phi - \mu \xi - (1 + \tau)(\sigma l + b) + \iota \left(1 + \frac{\beta f(\theta)}{r+\delta}\right) S_i}{r + s + \iota + \left(1 + \frac{\beta f(\theta)}{r+\delta}\right) \beta f(\theta)}. \] (21)

**Job creation by firms**

Using equations (3), (20) and (21), we obtain the job creation condition, which implies that the expected value to the firm of filling a position must, at equilibrium, be equal to the cost of opening the vacancy,

\[ \frac{c}{q(\theta)} = \lambda(1 - \beta)S_i + (1 - \lambda)(1 - \beta)S_e. \] (22)

Since \( \xi \) and \( l \) increase the surpluses \( S_i \) and \( S_e \), a higher level of on-the-job human capital increases the firms expected value, which induces them to post more vacancies. As a result,

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\(^8\)A more detailed exposition of the derivation of stationary equilibrium surpluses, wages, and on-the-job training and learning decisions can be found in Appendix A.
the labor market tightness (\(\theta\)) rises, which in turn increases both the job finding rate (\(f(\theta)\)) and, according to equation (19), the equilibrium employment rate \(n\).

**Equilibrium wage**

To find the equilibrium wages of fully-trained workers, we first calculate \(W_i - U_i\) using (7) and (9), and then we plug it in (11). After some manipulation, we obtain

\[
(1 + \tau)w_i = \beta Ae^\psi h^\phi + (1 - \beta)(1 + \tau)b + (1 - \beta)\beta f(\theta)\frac{\delta S_e + r S_i}{r + \delta}.
\]

(23)

Next, we calculate \(W_e - U_e\) using (6) and (8), then we plug it in (11). After some manipulation, we obtain the wage of newly-hired workers involved in on-the-job training and learning process

\[
(1 + \tau)w_e = \beta (Ae^\psi h^\phi - \mu \xi) + (1 - \beta)(1 + \tau)(b + \sigma l) + (1 - \beta)\beta f(\theta)\frac{(r + \delta + \tau)S_e - \tau S_i}{r + \delta}.
\]

(24)

Equations (23) and (24) show that on-the-job learning and training increase workers’ wages because they increase workers’ productivity. In turn, equation (24) shows that training costs \(\mu \xi\) have a direct negative effect on the wages of newly-hired workers involved in on-the-job human capital acquisition because firms transfer a fraction \(\beta\) of these costs to the workers in the form of lower wages. Similarly, learning costs \(\sigma l\) have a direct positive effect on \(w_e\) since workers transfer a fraction \((1 - \beta)\) of the learning costs to the firm.

**On-the-job training and on-the-job learning**

Assuming that both workers and firms choose the level of learning and training efficiently to maximize the value of a worker and an occupied position given the job market tightness \(\theta\), and using (6)-(8), the first-order conditions for the optimal level of on-the-job training and on-the-job learning yield

\[
\xi = \left( \frac{\Omega_2}{\mu} \right)^{\frac{1}{1 - \phi}},
\]

(25)

\[
l = \left( \frac{\Omega_2}{\sigma} \right)^{\frac{1}{1 - \phi}},
\]

(26)

where

\[
\Omega \equiv 1 + \frac{\tau}{r + s} + \frac{\tau}{r + s (r + \delta)(r + s) + r \beta f(\theta)}.
\]

(27)

Equations (25) and (26) show that training decisions \(\xi\) taken by the firm complement the efforts made by the workers in their on-the-job learning process \(l\). This complementarity
implies that training induces workers to increase their learning activities in the workplace to raise their wages, and then, to offset part of the training costs transferred from firms to workers. In turn, equation (27) shows that a higher finishing rate $\iota$ of the training and learning process and a lower rate $\delta$ of skill loss increase the return of both training and learning investments. Finally, note that $\Omega$ captures the discounted value of training and learning while the worker is being trained, while the worker is fully trained, and the discounted value of the portability of on-the-job human capital from job to job.

It is straightforward to see that, since formal education $\epsilon$ has a direct positive effect on the worker’s productivity, the surpluses of the job positions (20)-(21) increase, pushing up wages (23)-(24). In contrast, payroll taxes affect the employment opportunity cost (in line with previous literature, such as Prescott, 2004), reducing the job surplus and increasing wages. Moreover, $\epsilon$ and $\tau$ also modify the marginal costs of training and learning. In greater detail, taxes increase the implicit marginal cost of learning from $\sigma$ to $(1 + \tau)\sigma$ (equation 26), which reduces the level of learning $l$ and, by complementarity, brings down the level of training provided by the firm $\xi$. In turn, $\epsilon$ can also be interpreted as a reduction in the implicit marginal costs of training from $\mu$ to $\mu/\epsilon\psi$ and that of learning from $\sigma$ to $\sigma/\epsilon\psi$, which leads to higher training and learning investments, and to higher labor productivity (see equations (25)-(26)).

4 Calibration and simulated results

This section undertakes a quantitative assessment of the role of training and learning investments have on patterns observed in the on-the-job human capital acquisition, employment and productivity. First, we calibrate the model’s parameters using the average OECD economy as our benchmark economy. Second, we analyze the role of taxes and education to explain the variation in human capital acquired on the job, employment and productivity across the OECD countries. Third, we obtain the marginal costs in every country that reproduce the levels of on-the-job human capital as observed in the data. Finally, we analyze policy implications of training workers on the job.

4.1 Calibration

We calibrate the model at a quarterly frequency in order to match it with several empirical facts of the average OECD economy. Some of the targets and calibrated parameters correspond to the main year of the PIAAC (2012). Thus, our calibration is in line with the on-the-job human capital acquisition index presented in section 2. Table 1 summarizes all the calibrated parameters and presents the steady-state values of the endogenous variables.

The interest rate is set at $r = 0.012$, similar to Shimer (2005). Following Garda (2016), we
set \( s = 0.10^{0.25} = 0.045 \) to be consistent with an annual transition rate from employment to joblessness of 10\%.\(^9\) The matching function’s elasticity parameter with respect to unemployment is set at \( \alpha = 0.5 \), which is in the range of plausible values according to Petrongolo and Pissarides (2001).

Table 1: Calibrated parameter values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source/Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest rate, ( r )</td>
<td>0.012</td>
<td>Shimer (2005)</td>
</tr>
<tr>
<td>Separation rate, ( s )</td>
<td>0.045</td>
<td>Garda (2016)</td>
</tr>
<tr>
<td>Rate of skill loss, ( \delta )</td>
<td>0.039</td>
<td>Ortego-Marti (2017)</td>
</tr>
<tr>
<td>Acquisition rate of the OJHCA, ( \iota )</td>
<td>0.250</td>
<td>Silva and Toledo (2009)</td>
</tr>
<tr>
<td>Matching function scale, ( m_o )</td>
<td>0.085</td>
<td>Solves (2)</td>
</tr>
<tr>
<td>Matching function elasticity, ( \alpha )</td>
<td>0.500</td>
<td>Petrongolo and Pissarides (2001)</td>
</tr>
<tr>
<td>Workers’ bargaining power, ( \beta )</td>
<td>0.500</td>
<td>( \alpha = \beta ), Hosios (1990)</td>
</tr>
<tr>
<td>Productivity residual, ( A )</td>
<td>0.169</td>
<td>Solves ( y = A h^\phi )</td>
</tr>
<tr>
<td>Output elasticity w.r.t. OJHCA, ( \phi )</td>
<td>0.170</td>
<td>Konings and Vanormelingen (2015)</td>
</tr>
<tr>
<td>Output elasticity w.r.t. education, ( \psi )</td>
<td>0.330</td>
<td>Mankiw et al. (1992)</td>
</tr>
<tr>
<td>Marginal training costs, ( \mu )</td>
<td>0.025</td>
<td>Solves (25)-(26)</td>
</tr>
<tr>
<td>Marginal learning costs, ( \sigma )</td>
<td>0.013</td>
<td>Solves (25)-(26)</td>
</tr>
<tr>
<td>Cost of vacancy, ( c )</td>
<td>0.195</td>
<td>Solves (20)-(24), and ( NRR = 0.65 )</td>
</tr>
<tr>
<td>Employment opportunity cost, ( b )</td>
<td>0.454</td>
<td>Solves (20)-(24), and ( NRR = 0.65 )</td>
</tr>
</tbody>
</table>

Variable

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source/Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment rate, ( n )</td>
<td>0.655</td>
<td>OECD</td>
</tr>
<tr>
<td>Labor productivity, ( y )</td>
<td>1.000</td>
<td>Normalization</td>
</tr>
<tr>
<td>Labor market tightness, ( \theta )</td>
<td>1.000</td>
<td>Normalization</td>
</tr>
<tr>
<td>Job finding rate, ( f(\theta) )</td>
<td>0.085</td>
<td>Solves (19)</td>
</tr>
<tr>
<td>Incumbents unemployed share, ( \lambda_i )</td>
<td>0.653</td>
<td>Solves ( \lambda_i = \iota f(\theta)/(\iota f(\theta) + \delta (\iota + s)) )</td>
</tr>
<tr>
<td>Incumbents joblessness, ( u_i )</td>
<td>0.225</td>
<td>Solves ( u_i = \lambda_i (1 - n) )</td>
</tr>
<tr>
<td>Entrants joblessness, ( u_e )</td>
<td>0.120</td>
<td>Solves ( u_e = 1 - n - u_i )</td>
</tr>
<tr>
<td>Entrants employment, ( n_e )</td>
<td>0.035</td>
<td>Solves ( n_e = \delta u_i / \iota )</td>
</tr>
<tr>
<td>Incumbents employment, ( n_i )</td>
<td>0.620</td>
<td>Solves ( n_i = n - n_e )</td>
</tr>
<tr>
<td>Entrants surplus, ( S_e )</td>
<td>2.916</td>
<td>Solves (20)-(24), and ( NRR = 0.65 )</td>
</tr>
<tr>
<td>Incumbents surplus, ( S_i )</td>
<td>5.451</td>
<td>Solves (20)-(24), and ( NRR = 0.65 )</td>
</tr>
<tr>
<td>Entrants wage, ( w_e )</td>
<td>0.474</td>
<td>Solves (20)-(24), and ( NRR = 0.65 )</td>
</tr>
<tr>
<td>Incumbents wage, ( w_i )</td>
<td>0.710</td>
<td>Solves (20)-(24), and ( NRR = 0.65 )</td>
</tr>
<tr>
<td>On-the-job training index, ( \xi )</td>
<td>26.5</td>
<td>PIAAC</td>
</tr>
<tr>
<td>On-the-job learning index, ( \iota )</td>
<td>44.8</td>
<td>PIAAC</td>
</tr>
<tr>
<td>On-the-job human capital index, ( h )</td>
<td>34.5</td>
<td>PIAAC</td>
</tr>
</tbody>
</table>

We target an average employment-to-working-age population rate \( n = 65.5\% \) (OECD database) and, to be consistent with equation (19), we obtain a job finding rate of \( f(\theta) = 0.085 \). Similar to Shimer (2005), we normalize job market tightness to \( \theta = 1 \) and use the matching

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\(^9\)Joblessness includes transitions from employment to both unemployment and inactivity.
function (2) to obtain \( m_0 = f(\theta)/\theta^{1-\alpha} = 0.085 \). In addition, we set the workers’ bargaining power equal to the matching function elasticity at \( \beta = \alpha = 0.5 \), consistent with the Hosios (1990) efficiency condition.

Using wages information by sector from the U.S. Panel Study of Income Dynamics, Ortego-Marti (2017) shows that the monthly skill losses during unemployment vary significantly by industry (from 0.66% in Manufacturing to 1.81% in Wholesale, Retail trade). We use the OECD employment composition by industry to calculate an average quarterly rate of skill loss of \( \delta = 1 - (1 - 0.013)^3 = 0.039 \). Moreover, we set a rate \( \iota = 0.25 \) at which the workers finish the training and learning process implying a 1-year period of training and learning, which is consistent with the evidence presented in Silva and Toledo (2009).

We normalize labor productivity to 1 (\( y = A^\epsilon h^\phi = 1 \)). Then, we calibrate its components using OECD data for the average proportion \( \epsilon = 35.3\% \) of tertiary educated and payroll taxes \( \tau = 0.19 \), and PIAAC data for the average level of on-the-job training \( \xi = 26.6\% \), learning \( l = 44.8\% \) and human capital acquisition \( h = (\xi l)^{1/2} = 34.5\% \). Konings and Vanormelingen (2015) find that increasing the proportion of workers receiving training by 10% can increase productivity by 3.2% in Belgium, a country with similar values of training (26.6) and learning (45.0) to the OECD average. Then, we compute the implied elasticity \( \phi = 0.17 \) of output with respect to human capital as follows: \( \phi/2 = (\Delta y/y)/(\Delta \xi/\xi) = (0.032)/(10/26.6) \). Thus, the contribution of on-the-job human capital acquisition to labor productivity is \( h^\phi = 1.82 \). In addition, we use the elasticity \( \psi = 0.33 \) of output with respect to education following Mankiw et al. (1992), and compute its contribution to the labor productivity \( \epsilon^\psi = 35.3^{33} = 3.24 \). Hence, the residual labor productivity is \( A = 0.169 \), and marginal costs of training \( \mu = 0.025 \) and learning \( \sigma = 0.013 \) follow from equations (25) and (26).

The proportion \( \lambda_i = 0.653 \) (\( \lambda_i = u_i/u = \iota f(\theta)/(\iota f(\theta) + \delta(\iota + s)) \)) of unemployed workers whose skills acquired on the job are portable follows from combining equations (13), (15), (16), and (17) in equilibrium. Thus, the shares of unemployed are \( u_i = 0.225 \) and \( u_e = 0.12 \), and \( \lambda_e = u_e/u = 1 - \lambda_i = 0.347 \). Then, using equations (16) and (17), we obtain the share \( n_e = \delta u_i/\iota = 0.035 \) of employed in a position receiving training, and the share \( n_i = n - n_e = 0.62 \) of those fully trained.

Using the Benefit Statistics data from the OECD, we find an average net replacement rate (NRR) of 65% during the initial phase of unemployment in 2012. Finally, the equilibrium wages \( w_e = 0.474 \) and \( w_i = 0.71 \), the surpluses \( S_e = 2.916 \) and \( S_i = 5.451 \), the vacancy costs \( c = 0.195 \), and the unemployment benefits \( b = 0.454 \) are set to solve the equilibrium equations (20)-(24) and the target \( NRR = 0.65 \).
4.2 Quantitative assessment: education and taxes

Firstly, countries are treated as being identical to the benchmark economy except in their proportion of tertiary educated individuals ($\epsilon$) and payroll taxes ($\tau$). To explore the quantitative implications education and payroll taxes have on on-the-job human capital acquisition, employment and productivity, we use the parameters summarized in Table 1 for every country and let the variables of interest be determined by the model. Considering the exogenous variation in $\epsilon$ and $\tau$, we address the following question: how much of the observed differences in the OJHCA, employment rates, and productivity can be accounted for by the model?

Table 2: On-the-job human capital acquisition, employment and productivity: data and model

<table>
<thead>
<tr>
<th>Tertiary educated (%)</th>
<th>T3</th>
<th>T2</th>
<th>T1</th>
<th>T3-T2</th>
<th>T3-T1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payroll taxes</td>
<td>.111</td>
<td>.218</td>
<td>.251</td>
<td>-.107</td>
<td>-.140</td>
</tr>
</tbody>
</table>

Panel A

<table>
<thead>
<tr>
<th>OJHCA</th>
<th>Data</th>
<th>Model ($\epsilon$, $\tau$)</th>
<th>Education</th>
<th>Taxes</th>
</tr>
</thead>
<tbody>
<tr>
<td>T3</td>
<td>44.9</td>
<td>39.4</td>
<td>36.9</td>
<td>36.9</td>
</tr>
<tr>
<td>T2</td>
<td>36.4</td>
<td>35.0</td>
<td>35.8</td>
<td>33.6</td>
</tr>
<tr>
<td>T1</td>
<td>24.0</td>
<td>28.5</td>
<td>30.2</td>
<td>32.7</td>
</tr>
<tr>
<td>T3-T2</td>
<td>8.5</td>
<td>4.4</td>
<td>1.0</td>
<td>3.2</td>
</tr>
<tr>
<td>T3-T1</td>
<td>20.9</td>
<td>10.9</td>
<td>6.7</td>
<td>4.2</td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th>Employment</th>
<th>Data</th>
<th>Model ($\epsilon$, $\tau$)</th>
<th>Education</th>
<th>Taxes</th>
</tr>
</thead>
<tbody>
<tr>
<td>T3</td>
<td>71.1</td>
<td>68.8</td>
<td>67.2</td>
<td>67.3</td>
</tr>
<tr>
<td>T2</td>
<td>66.3</td>
<td>65.9</td>
<td>66.6</td>
<td>64.8</td>
</tr>
<tr>
<td>T1</td>
<td>58.9</td>
<td>59.1</td>
<td>61.5</td>
<td>63.9</td>
</tr>
<tr>
<td>T3-T2</td>
<td>4.8</td>
<td>2.9</td>
<td>0.7</td>
<td>2.5</td>
</tr>
<tr>
<td>T3-T1</td>
<td>12.2</td>
<td>9.7</td>
<td>5.8</td>
<td>3.4</td>
</tr>
</tbody>
</table>

Panel C

<table>
<thead>
<tr>
<th>Productivity</th>
<th>Data</th>
<th>Model ($\epsilon$, $\tau$)</th>
<th>Education</th>
<th>Taxes</th>
</tr>
</thead>
<tbody>
<tr>
<td>T3</td>
<td>1.11</td>
<td>1.06</td>
<td>1.05</td>
<td>1.01</td>
</tr>
<tr>
<td>T2</td>
<td>1.02</td>
<td>1.02</td>
<td>1.03</td>
<td>1.00</td>
</tr>
<tr>
<td>T1</td>
<td>0.87</td>
<td>0.91</td>
<td>0.92</td>
<td>0.99</td>
</tr>
<tr>
<td>T3/T2</td>
<td>1.09</td>
<td>1.04</td>
<td>1.02</td>
<td>1.02</td>
</tr>
<tr>
<td>T3/T1</td>
<td>1.27</td>
<td>1.17</td>
<td>1.14</td>
<td>1.02</td>
</tr>
<tr>
<td>Education and Taxes no OJHCA</td>
<td>1.04</td>
<td>1.04</td>
<td>1.01</td>
<td>1.01</td>
</tr>
</tbody>
</table>

Table 2 presents the simulation results and the values observed in the data and predicted by the model for the first (T1), the second (T2) and the third (T3) tertiles. The values are reported for the OJHCA, the employment rate, and labor productivity. Productivity values are
reported with respect to the average OECD economy, which we normalized to 1. Table 2 also includes information about the OJHCA and employment gaps between the third and second tertiles (T3-T2) and the third and first tertiles (T3-T1) of the OJHCA, and the productivity ratios between the third and second tertiles (T3/T2) and the third and first tertiles (T3/T1). Specifically, we compare the results for an average economy in each tertile of the OJHCA index distribution.\footnote{T1 includes 9 countries with the lowest values of OJHCA, T3 includes the highest 9, and T2 includes the 10 countries with the middle values. Ordered from the minimum to the maximum level of on-the-job human capital index, we find Turkey, Greece, Italy, Lithuania, Poland, Korea, France, Slovak Republic, and Slovenia in T1, Austria, Japan, Ireland, Spain, Belgium, Czech Republic, Israel, Estonia, Great Britain, and Germany in T2, and Sweden, Chile, Denmark, Canada, Netherlands, Finland, Norway, United States, and New Zealand in T3. See Table 4 in the Appendix for the values of different countries.}

The model performs quite well for both levels and differences. In particular, in Panel A of Table 2, we observe that the model accounts for 52% of the differences of OJHCA observed in the data between T3 and T2, and between T3 and T1. Hence, on average, taxes and education explain a large share of the differences observed among tertiles. Then, we decompose the role of taxes and education separately. Between the first and third tertile, education differences are more pronounced than tax differences, then, education accounts for 61% and taxes for 39%. In contrast, taxes account for 73% of the differences generated by the model between the third and second tertiles, while education for only 23%.\footnote{We can compute the elasticity \( (OJHCA_{T3} - OJHCA_{T1})/(X_{T3} - X_{T1}) \times (X_{T1})/(OJHCA_{T1}) \), where \( X \) is either the proportion of tertiary educated and taxes. We obtain that the elasticity of OJHCA with respect to taxes and education is -0.69 and 1.09, respectively.}

The results in terms of employment (Panel B of Table 2) reveal a similar picture. The model accounts for 80% of the differences between T3 and T1, and 60% between T3 and T2. Taxes alone account for most of the model differences between T3 and T2, while education plays a greater role than taxes to account for the differences between T3 and T1. To know whether the channel of OJHCA is important quantitatively, in last row of Panel B of Table 2 we do not allow the OJHCA to vary in the model simulations. We obtain that the direct effect of education and taxes on employment are 2.3 out of the 2.9 points between T3 and T2, and 7.3 out of 9.7 between T3 and T1, which implies that OJHCA explains 21% and 25% of the employment differences T3-T2 and T3-T1. Hence, this quantitative exercise reveals that an important part of the employment differences between countries, are consequence of payroll taxes and education through the effects on human capital acquisition at the workplace. In addition, the numerical analysis also reveals that increasing the proportion of individuals with tertiary education by 10.2 p.p. (from 29 to 39.2%) increases the employment rate 5.8 p.p., while reducing payroll taxes from 0.25 to 0.11 increases employment by 3.4 p.p. Hence, the model predicts that cutting taxes or increasing the share of tertiary educated by 1 p.p. increases the employment rate by 0.24 and 0.57 p.p., respectively.

Productivity results are presented in Panel C of Table 2. Both taxes and education play
a role in explaining productivity differences across tertiles but, in contrast to OJHCA and employment, taxes do not play a greater role than education in explaining the differences between T3 and T2. In line with OJHCA and employment, education does play a greater role than taxes in explaining productivity differences between countries in the first and third tertiles, and 41% of the effect of taxes and education is through OJHCA.

4.3 Quantitative assessment: training and learning marginal costs

In contrast to the previous subsection, here we allow countries to differ not only on taxes and education but also in the marginal costs of training and learning to quantify differences in employment and productivity across countries. In this case, countries are treated as being identical to the benchmark economy except in their proportion of tertiary educated individuals (\(\epsilon\)), payroll taxes (\(\tau\)), and marginal costs of learning (\(\sigma\)) and training (\(\mu\)).

Table 3: On-the-job human capital acquisition, employment and productivity: data and model (with and without variation of training and learning marginal costs)

Panel A

<table>
<thead>
<tr>
<th></th>
<th>OJHCA</th>
<th>T3</th>
<th>T2</th>
<th>T1</th>
<th>T3-T2</th>
<th>T3-T1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>44.9</td>
<td>36.4</td>
<td>24.0</td>
<td>8.5</td>
<td>20.9</td>
<td></td>
</tr>
<tr>
<td>Model ((\epsilon, \tau))</td>
<td>39.4</td>
<td>35.0</td>
<td>28.5</td>
<td>4.4</td>
<td>10.9</td>
<td></td>
</tr>
<tr>
<td>Model ((\epsilon, \tau, h))</td>
<td>44.9</td>
<td>36.4</td>
<td>24.0</td>
<td>8.5</td>
<td>20.9</td>
<td></td>
</tr>
</tbody>
</table>

Panel B

<table>
<thead>
<tr>
<th></th>
<th>Employment</th>
<th>T3</th>
<th>T2</th>
<th>T1</th>
<th>T3-T2</th>
<th>T3-T1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>71.1</td>
<td>66.3</td>
<td>58.9</td>
<td>4.8</td>
<td>12.2</td>
<td></td>
</tr>
<tr>
<td>Model ((\epsilon, \tau))</td>
<td>68.8</td>
<td>65.9</td>
<td>59.1</td>
<td>2.9</td>
<td>9.7</td>
<td></td>
</tr>
<tr>
<td>Model ((\epsilon, \tau, h))</td>
<td>69.5</td>
<td>66.2</td>
<td>57.2</td>
<td>3.4</td>
<td>12.3</td>
<td></td>
</tr>
</tbody>
</table>

Panel C

<table>
<thead>
<tr>
<th></th>
<th>Productivity</th>
<th>T3</th>
<th>T2</th>
<th>T1</th>
<th>T3/T2</th>
<th>T3/T1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data</td>
<td>1.11</td>
<td>1.02</td>
<td>0.87</td>
<td>1.09</td>
<td>1.27</td>
<td></td>
</tr>
<tr>
<td>Model ((\epsilon, \tau))</td>
<td>1.06</td>
<td>1.02</td>
<td>0.91</td>
<td>1.04</td>
<td>1.17</td>
<td></td>
</tr>
<tr>
<td>Model ((\epsilon, \tau, h))</td>
<td>1.08</td>
<td>1.03</td>
<td>0.88</td>
<td>1.05</td>
<td>1.23</td>
<td></td>
</tr>
</tbody>
</table>

Although the same level of human capital can be achieved through different levels of training and learning, we do not observe important differences between training and learning that lead to differences in employment rates neither in the data (see Figure 6 in Appendix) nor in the model. However, the variation of marginal costs improves the performance of the model to account for labor market differences. Panel A of Table 3 reproduces data values, simulated values with variation in education and taxes, and simulated values with additional
variation in marginal costs of training and learning to reproduce the variation of OJHCA in the data.

We use the parameters summarized in Table 1 and equations (25) and (26) to compute the marginal costs of training and learning that generate the level of OJHCA $h$ observed in every country. Hence, we target the levels of OJHCA in T1, T2 and T3, and obtain marginal costs of training and learning to be 13% greater in T1 than in the average economy, 3% lower in T2 than in the average, and 9% lower in T3 than in the average. Introducing variation in marginal costs, allows the model simulations to account better for differences in employment and productivity across tertiles. Specifically, the model accounts for 71% (T3-T2) and 101% (T3-T1) of employment differences, and 96% (T3/T2) and 97% (T3/T1) of productivity ratios.

### 4.4 Quantitative assessment: cross-country differences

Figure 3: Employment and productivity against OJHCA: data and model

(a) Employment and OJHCA

(b) GDP per worker and OJHCA

Following the approach of the last subsection with variation in education, taxes and marginal costs of training and learning, we now turn to look at country-level predictions. Hence, we take the values of tertiary educated and taxes for every country, and find marginal costs of training and learning that reproduce the index of OJHCA in every country. In this case, the number of model simulations is lower than observations because there is no tax data for Lithuania and Turkey, and the low proportion of tertiary educated individuals in Italy generates model simulations that are not reliable. Table 5 in the Appendix shows the simulated values and estimated marginal costs relative to the average. The left panel of Figure 3 shows the data versus the simulated values of employment rates, while the right panel shows the values of productivity. In general, the model performs well in explaining the positive relationship observed in the data between human capital with employment and productivity.
Moreover, the model is able to match the average differences in employment rates and productivity between different levels of human capital. In particular, the slopes of the regression line of the data and the simulated values are .570 and .572, respectively, for employment, and .009 and .008 for labor productivity. Moreover, more than 20 out of the 25 countries, show a difference between the simulated and the actual values of employment lower than 5 p.p.

Figure 4: Employment and productivity against education and payroll taxes: data and model

Figure 4 shows the relationships between education and taxes with employment and productivity. The model simulations perform quite well to reproduce the relationships between the share of tertiary educated and productivity (Panel C), although model variation is lower than data. In terms of taxes, the model introduces a small negative relationship between taxes and productivity (Panel D) that is not present in the data. With regard to the correlation with employment, the model performs well to reproduce the data relationships in both cases of education and taxes (Panels A and B). Last but not least, we find it convenient to highlight that the model with variations in taxes and education and constant marginal costs presented
in subsection 4.2 is able to match quite well the positive relationships between OJHCA, employment, and productivity with the share of tertiary educated, and the negative relationships between OJHCA, employment and productivity with payroll taxes (see Figure 7 in Appendix).

4.5 Quantitative assessment: subsidizing training costs

In this section, we analyze the effects of adjusting the marginal costs of training ($\mu$). We consider the OECD average economy in terms of education, taxes and costs of training and learning, among other variables, and modify the cost of training to shed some light on the effects of subsidizing training costs for firms. In contrast to the previous exercises, we do not alter marginal learning costs.

The left Panel of Figure 5 shows the changes in training, learning and human capital predicted by the model, when the marginal costs of training are modified exogenously. Increasing marginal training costs reduces human capital not only because training falls but also because learning decreases, whereas reducing marginal training costs generate the opposite effects. The complementarity between training and learning observed in the data and captured in equations (25) and (26) of the model explains the relationships shown in our simulation. Hence, our model is able to rationalize the fact that policies targeted at reducing marginal training costs $\mu$ can help accumulate human capital, raise labor productivity and increase the employment rate, taking into account the complementarity between training and learning. More precisely, our simulations show that a 10% reduction in marginal costs of training generates an increase of 2.5 points in the OJHCA index and, as a result, a 0.5 percent points increase in the employment rate (see the right Panel of Figure 5).

Figure 5: OJHCA and employment against marginal training costs

(a) OJHCA and marginal costs
(b) Employment and marginal costs
5 Conclusion

In a globalized world competitiveness is a key element for economic development and, on-the-job human capital acquisition can be considered as an essential tool. This happens in a context in which workforce skills are increasingly gaining in importance, thus requiring firms and workers alike to adapt to the use of more complex technologies. Against this backdrop, it is crucial improve our understanding of the way in which the different components of human capital -including, formal on-the-job training and workers’ on-the-job learning- affect labor market outcomes.

In this paper, we explore the role of on-the-job human capital acquisition in explaining differences in employment among OECD countries. We build an index of on-the-job Human Capital Acquisition for 28 OECD economies using PIAAC data. The index, which combines formal on-the-job training and informal learning in the workplace, reveals substantial variations across countries and it is positively correlated with employment rates. On top of that, the two components of the human capital index, on-the-job training and on-the-job learning, show a strong positive correlation.

To explain these raw stylized facts, we build a search and matching model incorporating on-the-job human capital acquisition that depends on both on the job training determined by firms and workers’ decisions regarding on the job learning. We consider two important factors that can affect human capital acquisition, productivity and employment: formal education and payroll taxes. While education increases human capital investments because it raises productivity, payroll taxes decrease human capital investments because the opportunity costs of employment and the cost of learning rise.

To quantify the employment effects skills acquired at the workplace have, we calibrate the model to the OECD average economy. We decompose the effect of education and payroll taxes to determine differences in on-the-job human capital acquisition, productivity, and employment. We find that taxes and education explain more than half of the variation in on-the-job skill acquisition and employment. We also find that payroll taxes contribute more than education to explain the differences between countries in the high part of the distribution of the human capital index, while education plays a greater role than payroll taxes in explaining the differences between countries in the bottom part of the distribution. Moreover, the quantitative exercise reveals that an important proportion (between 21% to 25%) of the employment effects of payroll taxes and education is through the acquisition of human capital at the workplace.

We finally adjust the learning and training marginal costs to match the observed cross-country levels in the human capital index, which enables the model to reproduce differences in productivity and employment rates across countries. The model predicts that a 1 p.p. increase in the share of population with tertiary education implies a 0.57 p.p. increase in the
employment rate. On the other hand, reducing employer payroll taxes by 1 p.p. increases
the employment rate by 0.24 p.p. and, finally, reducing training marginal costs by 10% would
increase the share of trained workers by 3.5 p.p., workers learning at their workplace by 1 p.p.,
and the employment rate by 0.5 p.p.

References

Acemoglu, Daron and Jorn-Steffen Pischke, “Beyond Becker: Training in Imperfect

_ and _, “The Structure of Wages and Investment in General Training,” *Journal of Political

Arrow, Kenneth J., “The Economic Implications of Learning by Doing,” *Review of Eco-

Barron, John, Mark Berger, and Dan Black, *On-the-Job Training*, W.E. Upjohn Insti-


Bishop, John H., “What we know about employer-provided training: A review of literature,”
CAHRS Working Paper 96-09, Ithaca, NY: Cornell University, School of Industrial and
Labor Relations, Center for Advanced Human Resource Studies. 1996.

Cairó, Isabel and Tomaz Cajner, “Human Capital and Unemployment Dynamics: Why
2018, 128 (609), 652–682.

Destré, Guillaume, Louis Lévy-Garboua, and Michel Sollogoub, “Learning from ex-
perience or learning from others?: Inferring informal training from a human capital earnings
function with matched employer-employee data,” *Journal of Behavioral and Experimental

Ferreira, Maria, Andries de Grip, and Rolf van der Velden, “Does informal learn-
ing at work differ between temporary and permanent workers? Evidence from 20 OECD

_ , Annemarie Kün-Nelen, and Andries De Grip, “Work-Related Learning and Skill
Development in Europe: Does Initial Skill Mismatch Matter?,” in “Skill Mismatch in Labor
pp. 345–407.

Grip, A De, “The importance of informal learning at work,” IZA World of Labor 162, IZA 2015.


Appendix

A Stationary equilibrium equations

This section describes the steps taken to obtain the equations in section 3.3.

A.1 Surplus

To obtain the surplus expressions (20) and (21), first notice that from (6), (7), and the surplus sharing rule \((1 + \tau)(W_k - U_k) = \beta S_k\) for \(k = e, i\), we obtain

\[
(1 + \tau)(U_i - U_e) = \frac{\beta f(\theta)(S_i - S_e)}{r + \delta}.
\] (28)

Then, plugging in expressions (5), (7) and (9) into \(S_i = J_i + (1 + \tau)(W_i - U_i)\), it follows that

\[
rS_i = r(J_i + (1 + \tau)(W_i - rU_i))
= y - (1 + \tau)b - s(J_i + (1 + \tau)(W_i - rU_i)) - \beta f(\theta)S_i + \delta(1 + \tau)(U_i - U_e),
\] (29)

where \(y = A\epsilon^\psi(\xi l)^\phi\). Then, plugging in (28) into (29) and rearranging terms we obtain

\[
S_i = \frac{A\epsilon^\psi(\xi l)^\phi - (1 + \tau)b - \frac{\delta}{r + \delta}\beta f(\theta)S_e}{r + s + \beta f(\theta)\frac{r}{r + \delta}}.
\]

Similarly, we use (4), (6), (8), (28) and \(S_k = J_k + (1 + \tau)(W_k - U_k)\) for \(k = e, i\) to obtain

\[
rS_e = y - \mu \xi - (1 + \tau)\sigma l - (1 + \tau)b - (s + \beta f(\theta))S_e + \iota(J_i - J_e + (1 + \tau)(W_i - W_e))
= y - \mu \xi - (1 + \tau)(\sigma l + b) - (s + \beta f(\theta))S_e + \iota\left(1 + \frac{\beta f(\theta)}{r + \delta}\right)(S_i - S_e),
\]

which can be rewritten as

\[
S_e = \frac{A\epsilon^\psi(\xi l)^\phi - \mu \xi - (1 + \tau)(\sigma l + b) + \iota\left(1 + \frac{\beta f(\theta)}{r + \delta}\right)S_i}{r + s + \iota + \beta f(\theta)\left(1 + \frac{r}{r + \delta}\right)}.
\]

A.2 Wages

To obtain wage expressions (23) and (24), we plug (5) and (9) in (11) and obtain

\[
\beta J_i = (1 - \beta)(1 + \tau)(W_i - U_i) \Leftrightarrow \beta\left(\frac{y - (1 + \tau)w_i}{r + s}\right) = (1 - \beta)(1 + \tau)\left(\frac{w_i - rU_i}{r + s}\right).
\]

Thus,

\[(1 + \tau)w_i = \beta y + (1 - \beta)r(1 + \tau)U_i\]

\[= \beta y + (1 - \beta)(1 + \tau)(b + f(\theta)(W_i - U_i) - \delta(U_i - U_e))\]

\[= \beta y + (1 - \beta)\left((1 + \tau)b + \beta f(\theta)S_i - \frac{\delta}{r + \delta}\beta f(\theta)(S_i - S_e)\right)\]

\[= \beta y + (1 - \beta)(1 + \tau)\left(b + \beta(1 - \beta)f(\theta)\right) + \frac{\delta}{r + \delta}(\delta S_e + rS_i),\]

where we use (7) and (28) to go from the first to the second and third lines, respectively.

Similarly, we use (4), (8), and (11) and obtain

\[\beta J_e = (1 - \beta)(1 + \tau)(W_e - U_e) \iff \beta \left(y - (1 + \tau)\frac{w_e - \mu \xi + iJ_i}{r + s + \iota}\right) = (1 - \beta)(1 + \tau)\left(\frac{w_e - \sigma l + iW_i - (r + \iota)U_e}{r + s + \iota}\right).\]

Next, we rewrite it and use (6) to obtain

\[(1 + \tau)w_e = \beta(y - \mu \xi) + (1 - \beta)(1 + \tau)(b + \sigma l + f(\theta)(W_e - U_e))\]

\[+ \iota(\beta J_i - (1 - \beta)(1 + \tau)(W_i - U_e))\]

\[= \beta(y - \mu \xi) + (1 - \beta)((1 + \tau)b + \sigma l + \beta f(\theta)S_e)\]

\[+ \iota(\beta J_i - (1 - \beta)(1 + \tau)(W_i - U_e))\]

\[= \beta(y - \mu \xi) + (1 - \beta)((1 + \tau)b + \sigma l + \beta f(\theta)S_e)\]

\[+ \iota(1 - \beta)(1 + \tau)(U_e - U_i)\]

\[= \beta(y - \mu \xi) + (1 - \beta)(1 + \tau)b + \sigma l\]

\[+ \beta(1 - \beta)\frac{f(\theta)}{r + \delta}((r + \delta + \iota)S_e - \iota S_i)\]

where we use (1 + \tau)(W_e - U_e) = \beta S_e, (11) and (28) and to go from the first to the second, third and fourth lines, respectively.

### A.3 On-the-job training and learning

Firms choose training \(\xi\) to maximize the value of an occupied job position \(J_e\),

\[\arg \max_{\xi} J_e = \arg \max_{\xi} y - (1 + \tau)w_e - \mu \xi + iJ_i,\]

where \(y = Ae^{\psi}(\xi l)^{\frac{\eta}{2}}\). Notice that since \((1 - \beta)S_e = J_e\), then \(\partial S_e/\partial \xi = 0\) because the first order condition (FOC) to the maximization problem implies \(\partial J_e/\partial \xi = 0\). Similarly, taking
into account that \( \partial U_e/\partial \xi = 0 \), then \( \partial W_e/\partial \xi = 0 \). Next, we obtain from expression (30) above that
\[
(1 + \tau) \frac{\partial w_e}{\partial \xi} = \beta \left( \frac{\partial y}{\partial \xi} - \mu + \nu \frac{\partial J_i}{\partial \xi} \right) - (1 - \beta)(1 + \tau) \frac{\partial W_i}{\partial \xi}.
\]

Then, the FOC to the maximization problem (31) simplifies to
\[
\mu = \frac{\partial y}{\partial \xi} + \nu \left( \frac{\partial J_i}{\partial \xi} + (1 + \tau) \frac{\partial W_i}{\partial \xi} \right) = \left( 1 + \frac{\nu}{r + s} \right) \frac{\partial y}{\partial \xi} + \frac{\nu s (1 + \tau)}{r + s} \frac{\partial W_i}{\partial \xi} = \frac{\Omega}{\partial y}{\partial \xi},
\]
where we use
\[
\frac{\partial J_i}{\partial \xi} + (1 + \tau) \frac{\partial W_i}{\partial \xi} = \frac{1}{r + s} \left( \frac{\partial y}{\partial \xi} - (1 + \tau) \frac{\partial w_i}{\partial \xi} \right) + \frac{1 + \tau}{r + s} \left( \frac{\partial w_i}{\partial \xi} + s \frac{\partial U_i}{\partial \xi} \right),
\]
\[
(1 + \tau) \frac{\partial U_i}{\partial \xi} = \frac{\beta f(\theta)}{r + s} \frac{\partial S_i}{\partial \xi} = \frac{\beta f(\theta)}{r + s} \frac{1}{r + s} \frac{\partial y}{\partial \xi},
\]
and
\[
\Omega \equiv 1 + \frac{\nu}{r + s} + \frac{\nu s f(\theta)}{r + s + \delta + s} = \frac{\beta f(\theta)}{r + s} \frac{1}{r + s} \frac{\partial y}{\partial \xi}.
\]

Expression (33) follows from the derivative of (28) with respect to \( \xi \) and taking into account that \( \partial S_e/\partial \xi = 0 \) and \( \partial U_e/\partial \xi = 0 \); \( \Omega \) captures the value of training over productivity while the worker is being trained, while the worker is fully trained, and the portability of skills to other jobs. We finally obtain (25) in the text plugging in the derivative of output \( y \) with respect to training \( \xi \) into equation (32) above
\[
\mu = \Omega \frac{\partial y}{\partial \xi} \Leftrightarrow \mu = \Omega A e^{\psi} \phi \frac{\partial \xi}{\partial \xi} \Leftrightarrow \xi = \left( \frac{\Omega - \psi}{2} \frac{A e^{\psi}}{\mu} \phi \right)^{\frac{1}{2}}.
\]

Equivalent to firms choosing training, workers choose learning \( l \) to maximize the value of a working position \( W_e \),
\[
\arg \max_{l} W_e = \arg \max_{\xi} w_e - \sigma l + i W_i + s U_e.
\]

Notice that since \( \beta S_e = W_e - U_e \), then \( \partial S_e/\partial l = 0 \), because the FOC to (34) implies \( \partial W_e/\partial l = 0 \), and \( \partial U_e/\partial l = 0 \). Hence, from expression (30) we obtain
\[
(1 + \tau) \frac{\partial w_e}{\partial l} = \beta \left( \frac{\partial y}{\partial l} + \nu \frac{\partial J_i}{\partial l} \right) + (1 - \beta)(1 + \tau) \left( \sigma - \nu \frac{\partial W_i}{\partial l} \right).
\]
Next, the FOC to the maximization problem \( (34) \) simplifies to

\[
(1 + \tau)\sigma = \frac{\partial y}{\partial l} + \left( \frac{\partial J_i}{\partial l} + (1 + \tau) \frac{\partial W_i}{\partial l} \right) = \left( 1 + \frac{\iota}{r + s} \right) \frac{\partial y}{\partial l} + \frac{\iota s (1 + \tau)}{r + s} \frac{\partial U_i}{\partial l} = \Omega \frac{\partial y}{\partial l},
\]

where we use

\[
\frac{\partial J_i}{\partial l} + (1 + \tau) \frac{\partial W_i}{\partial l} = \frac{1}{r + s} \left( \frac{\partial y}{\partial l} - (1 + \tau) \frac{\partial w_i}{\partial l} \right) + \frac{1 + \tau}{r + s} \left( \frac{\partial w_i}{\partial l} + s \frac{\partial U_i}{\partial l} \right),
\]

and

\[
(1 + \tau) \frac{\partial U_i}{\partial l} = \beta f(\theta) \frac{\partial S_i}{\partial l} = \beta f(\theta) \frac{1}{r + \delta} \frac{\partial y}{\partial l}.
\]

Finally, expression \((26)\) in the text follows

\[
(1 + \tau)\sigma = \Omega \frac{\partial y}{\partial l} \iff l = \left( \Omega \frac{\phi}{2 (1 + \tau)\sigma^\phi} \right)^{\frac{1}{1-\frac{\phi}{2}}}.
\]
### B Figures and Tables

Table 4: On-the-job human capital, training and learning indexes

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Source: Based on PIAAC data.
Table 5: Country values: OECD data and simulations

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1 The values are relative to the OECD average.
Figure 6: OJHCA, employment, learning and training

(a) On-the-job learning

(b) On-the-job training
Figure 7: OJHCA, employment, and productivity against education and payroll taxes: data and model

(a) OJHCA and education

(b) OJHCA and payroll taxes

(c) Employment and education

(d) Employment and payroll taxes

(e) Productivity and education

(f) Productivity and payroll taxes