



OECD Science, Technology and Industry Working Papers
2015/09

Estimating Cross-Country
Investment in Training: An
Experimental Methodology
Using PIAAC Data

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<https://dx.doi.org/10.1787/5jrs3sftp8nw-en>

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ESTIMATING CROSS-COUNTRY INVESTMENT IN TRAINING: AN EXPERIMENTAL METHODOLOGY USING PIAAC DATA

Mariagrazia Squicciarini^(*), Luca Marcolin^(*), and Peter Horvát^(†)

ABSTRACT

The present work proposes a novel methodology for the measurement of investment in human capital in the form of training. Differently from existing studies, the expenditures-based approach pursued encompasses investment in formal and on-the-job training, as well as in informal learning and yields estimates that account for both the opportunity and the direct cost of the different forms of training considered. Using a wide array of data sources, including new and rich individual-level data collected through the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey as well as Labour Force Surveys (LFS) and System of National Accounts (SNA) data, the study proposes estimates of investment in training for the years 2011-2012. These cover 22 OECD countries and are provided at both the economy and industry levels. Estimates suggest that average total investment in training corresponds to 6.7% of gross value added (GVA), with investment in on-the-job training (amounting to 2.4% of GVA, on average) that are substantially in line with those of previous literature. Wide sector and country heterogeneity in the relative importance of investment in formal and on-the-job and informal learning also emerge. On average, production appears more intensive in on-the-job training (relative to other training types) than overall services, but not relative to business services only. Public-oriented services such as education and health services invest a greater (smaller) proportion of total training expenditure in formal (on-the-job) training than other sectors and the overall economy.

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Acknowledgements: We are grateful to Aviana Bulgarelli, Alessandra Colecchia, Stephanie Jamet, Mary O'Mahony William Thorn, and all the participants to the SPINTAN mid-term conference held in London on April 23-24, 2015 and to the New Directions in Human Capital Theory workshop held at University of Birmingham on June 25-26, 2015, the OECD-PIAAC team, as well as the country delegates to the OECD Working Party on Industry Analysis (WPIA) for helpful comments and for providing feedback on earlier versions of this paper. The help of Colin Webb and of the OECD-STAN team, especially with respect to the data collection process, is also gratefully acknowledged. The usual caveats apply.

EXECUTIVE SUMMARY

Scholars and policy makers alike have long emphasised the key role that human capital plays in the generation and accumulation of knowledge-based capital (KBC) and in fostering economic growth and development. However, measuring investment in KBC to inform a wide array of policies aimed at empowering human remains a challenging and unfinished task.

This work contributes to address such a shortcoming by proposing an experimental methodology for the estimation of investment in human capital in the form of firm-relevant training. It exploits individual-level information contained in the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey about the extent to which workers engages in training; where and when such training takes place, i.e. within the firm or elsewhere, and during or outside working hours; who pays for the training; and about the usefulness of training for their current occupations.

Differently from existing studies, which take a single-country or European perspective and focus mostly on vocational training, it provides industry- and county-level estimates for 22 OECD countries for the years 2011-2012 and distinguishes between formal training, on-the-job training (i.e. vocational training) and informal learning. Such a characterisation is based on information related to the way in which training is administered (e.g. at the firm's premises or elsewhere); whether or not it leads to a degree (e.g. university degree); and the extent to which training occurs in a structured or unstructured fashion (e.g. formally scheduled lectures or informal meetings with superiors and peers).

Estimates rely on an expenditure-based approach whereby investment in training is calculated as a function of the hours that individuals spend in training and of their salaries (i.e. the opportunity cost of training), and of the cost that private entities and/or public institutions incur to provide the training (i.e. the direct cost of training). Such direct and indirect costs of training are discounted using information on: the extent to which firms pay for the training and allow it to happen during working hours; and the workers' perceived usefulness of the training. These elements are interpreted as signals that companies deem the training useful or needed, and that training is likely to enhance the productivity of companies - conditions which are both necessary for training to be considered as investment in KBC.

The resulting training figures, which rely on a number of industry and country-level data sources in addition to PIAAC data, are comparable across countries and industries, and are coherent with the System of National Accounts (SNA), with existing studies and with the measurement of other KBC-assets, as proposed in the Corrado, Hulten and Sichel (2005, 2009) framework. Also, using information from the PIAAC survey, this work proposes first-time experimental estimates of investment in training in the private and public sectors, thus contributing to shed light on the extent to which the public sector invests in knowledge-based capital.

Evidence suggests that while countries differ in the extent to which the workforce engages in formal and on-the-job training and in informal learning, it is high-skilled workers that mostly engage in it. Also, across all countries considered, around 90% or more of the workforce appears to have benefitted from some type of informal learning and most workers have engaged in several types of training. In terms of investment, on-the-job (i.e. vocational) training accounts for approximately 40% of total investment in training, and formal training on average exceeds this proportion and is even more relevant in a subgroup of countries.

While wide industry and country heterogeneities emerge in terms of overall investment in training, production generally appear as being more intensive in on-the-job training than services, with the exception of business services. Public services result especially intensive in formal training, in terms of

both incidence and amount invested. Industries as finance, ICT and health, education and social services display especially low percentages of trained employees who are low-skilled.

Public employees in sectors where public employment is most pronounced are more frequently recipients of on-the-job training than workers employed in private entities in market sectors and the average worker in the economy. This is not the case for formal training and informal learning. The public sector also invests more in training (as a percentage of gross value added) than the private sector and the overall economy.

This work confirms the importance of finding ways to better measure KBC, especially human capital-related investment, and to shed light on industry-specific behaviours as well as countries' heterogeneity. It further highlights the inadequacy of estimating investment in KBC using parameters inferred from analyses based on reference countries or industries. More importantly, though, it offers new evidence about the extent to which the workforce engages in training and the type of workers that mostly benefit from it. These estimates, and the possible future refinements that might be envisaged, will help inform the debate on a wide array of policy-relevant issues. These include: job quality and job mismatch; the contribution of investment in KBC, especially in training, to labour productivity; the ways in which investment in KBC might shape the transformation of production systems; the extent to which investment in different types of KBC as organisational capital, Information and Communication Technologies (ICT) and training happen in a complementary fashion; and how investment in KBC relate to participation and positioning in global value chains.

TABLE OF CONTENTS

OECD SCIENCE, TECHNOLOGY AND INDUSTRY WORKING PAPERS.....	1
ABSTRACT	2
EXECUTIVE SUMMARY	3
ESTIMATING CROSS-COUNTRY INVESTMENT IN TRAINING: AN EXPERIMENTAL METHODOLOGY USING PIAAC DATA.....	6
Introduction.....	6
Defining and measuring investment in training: a review	7
Typifying training	7
Existing approaches to the measurement of firm-specific training	8
What drives investment in training?	8
Employees’ and employers’ incentives to invest in training.....	9
Industry structure, firm characteristics, and training.....	11
Measuring training: an expenditure–based approach.....	12
Data sources: linking PIAAC to national data.....	13
Measuring training: a PIAAC-based methodology.....	15
Investment in “formal training”, “on-the-job training” and “informal learning”	15
Direct and opportunity costs of training.....	16
Formal training.....	19
On-the-job training.....	21
Informal learning.....	24
Public vs private sector investment in training	27
Investment in formal and on-the-job training and in informal learning: first descriptive evidence	28
Incidence of training.....	28
Investment in training.....	34
Public investment	39
Robustness checks	40
Main findings and future work	45
REFERENCES.....	47
ANNEX 1	52
ANNEX 2	54
ANNEX 3: FURTHER RESULTS	61
Boxes	
Box 1. Combining PIAAC and external data sources.....	133
Box 2. The direct cost of on-the-job training.....	22

ESTIMATING CROSS-COUNTRY INVESTMENT IN TRAINING: AN EXPERIMENTAL METHODOLOGY USING PIAAC DATA

Introduction

Knowledge-based capital (KBC), which comprises assets that are knowledge-intensive and lack physical embodiment, such as R&D or organisational capital, is becoming increasingly important both as a share of total business investment, and as a contributor to productivity and economic growth (see OECD, 2013a; Jona-Lasinio et al., 2011; Marrocu et al., 2011; and Corrado et al., 2012, for recent evidence). For instance, Corrado et al. (2013) report that intangible (vs tangible) capital deepening accounts for 23.8% (vs 41.6%) of labour productivity growth between 1995 and 2007 in Europe (GDP weighted average), and 31.9% (vs 26.8%) in the U.S..

While the many KBC definitions that exist (e.g. Choong, 2008; Corrado et al., 2009) emphasise the key role that human capital plays in the generation and accumulation of KBC and in fostering economic growth and development (Galor and Moav, 2004), measuring investment in human capital remains an unfinished and challenging task. Investment in human capital in fact encompasses, among others, education, training, and medical care (Becker, 1994), and these forms of investment vary in terms of nature, main characteristics and prospect returns.

The present work contributes to address this shortcoming by proposing a novel methodology for the measurement of investment in human capital in the form of training of employees. Human capital is here defined following de la Fuente and Ciccone (2003), as the set of knowledge and skills obtained through schooling, training and every day experience that are useful in the production of goods, services and further knowledge (see also Wright and McMahan, 2011, about human capital).

The proposed methodology builds on new and rich individual-level information collected through the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey. It builds on the work of O'Mahony (2012) and improves on it by encompassing investment in three forms of training, namely formal and on-the-job training as well as informal learning. The proposed estimates cover 22 OECD countries, at both the economy and industry levels. Contrary to existing estimates, this work relies on data collected via harmonised questionnaires and definitions of training and account for both the opportunity and the direct cost of each of the forms of training considered. Lastly, the presented methodology allows to separately estimate investment in training carried out by private and public entities, whereas established measures of KBC investment usually refer to the market sector only.

The first section of the paper summarises existing approaches to measuring firm-specific training. The second section discusses what drives investment in training, typifies the different types of training, and considers the industry- and firm-specific features that may shape such investment. A description of the proposed expenditure-based approach and of its main assumptions follows, including a detailed account of the way in which formal and on-the-job training and informal learning are estimated. The data used for the analysis are then outlined. A description of the sample in terms of frequency of training by skill, training type and industry precedes the estimates of investment in the different forms of training for 22 countries, at the industry and country-wide level, and by the private and public sectors. Some robustness checks are shown before concluding by briefly discussing some analytical paths that could be explored using these new estimates of investment in training.

Defining and measuring investment in training: a review

Typifying training

To try and estimate investment in training as accurately and completely as possible, it is necessary to distinguish and account for different types of workforce training.

The present study distinguishes between “formal training”, “on-the-job training” and “informal learning”. Formal training refers to training taking place in an organised, outside-work environment, and aiming at the attainment of a degree at an education institution (e.g. university degrees as MSc or BA). On-the-job training is a structured type of training that may take place both inside and outside a company (e.g. computer programming at a vocational education-type of institution). On-the-job training does not typically lead to the attainment of an education degree, and may take place during or outside working hours. Finally, informal learning results from the daily activities of employees at the workplace, and can be understood as learning by doing or learning from peers and/or supervisors.

Neither informal learning nor on-the-job training require enrolling in the formal education system, and only informal learning certainly takes place on the job according to the data available for this study. Informal learning is not included in the usual definition of on-the-job training (e.g. Barron et al., 1997), as it typically lacks an organised structure. On-the-job training, however, can also be carried out outside working hours and the working space. As a consequence, informal learning and on-the-job training together certainly account for more than what is usually understood as on-the-job training.

Existing work from Werquin (2007) and CEDEFOP (2014) also takes into account all three types of training, but differences in definitions exist between these studies and the present analysis. According to CEDEFOP (2014) informal learning can also happen outside the working environment, while this is not the case in the context of the present study; and on-the-job learning is usually not explicitly designed as learning, while it can be here. Also, for CEDEFOP (2014) formal learning can happen at the work place if sufficiently structured, whereas this is not the case in this analysis¹.

The three types of training contemplated in this study are by no means to be considered as mutually exclusive in nature or time. In particular, as informal learning often pertains to acquiring firms-specific capabilities and information, it may occur in the presence or absence of other types of training.

Informal learning has proved especially hard to measure, in light of its non-organised, non-structured nature (Bassanini et al., 2007). Barron et al. (1989) provide evidence for the U.S. whereby newly recruited employees declared to have received 96% of their training on the job in an informal way from peers. Using French data from 1992, Destré et al. (2008) highlight that informal learning in the form of learning by doing and learning from peers can increase an employee’s human capital by 10% with respect to the employee’s capital level upon joining the company. This accumulation of human capital is decreasing with the employee’s tenure, i.e. with the learning opportunity from others. Finally, informal learning is found to be very heterogeneous across firms and occupations.

The most recent evidence relating to informal learning is reported by de Grip and Sauermann (2012) who ran a randomised experiment involving teams of call centres’ employees of a Dutch telecommunication company. Call centres were chosen on purpose, as they display high levels of information exchanges among colleagues. The authors confirm the existence of training externalities by which employees who did not receive any “formal” training also increase their productivity.

¹ It could to some extent be if formal education is pursued through online courses or distance learning.

Existing approaches to the measurement of firm-specific training

The measurement of firm specific training at the macroeconomic level has mainly followed two approaches. These studies generally take into account only on-the-job training, as formal education is considered as a source of general knowledge and skills, whereas vocational education is seen as a source of firm-specific skills.

The first approach relies on data from national surveys to gather information about vocational training and apprenticeship. This is the approach followed, for instance, by Corrado et al. (2012), who measure total investment in training as the sum of firms' investment in vocational training and investment in apprenticeships using data from the Continuous Vocational Training (CVT) survey, from National Accounts and from Labour Cost Survey. Clayton et al. (2009) similarly estimate firm specific human capital expenditure for the United Kingdom using the National Employer Skills Survey. A recent extension of this approach (Corrado et al., 2015) focuses on the estimation of KBC investment by public and non-market entities.

The second approach generally relies on the European Labour Force Survey (LFS) and estimates investment in training as the sum of the direct expenditures incurred for the training and the opportunity costs of training. The most important contribution in this respect is by O'Mahony (2012) who combines data from LFS and the Continuous Vocational Training Survey and estimates total investment in vocational training. This corresponds to the product of the hours spent in training and the hourly cost of training, with the hourly cost of training composed of the direct cost of training and the opportunity cost of the forgone production or leisure time.

The approaches above appear somewhat narrow in light of the evidence provided by PIAAC, as many firms do invest in formal education as well. This may to some extent appear surprising, given the literature considering formal training as typically being of a "general" nature, and therefore a type of training that should not be firm-specific and that is easily transferrable to other companies. But formal training could increase the marginal productivity of workers more than their salaries, independently of its general or specific nature, thus justifying employers' investment. Furthermore, training cannot be defined as strictly specific or general in nature in the same way as knowledge is neither strictly general nor specific. Even training that is considered to be general can have a firm-specific component, at least to some extent (Loewenstein and Spletzer, 1999). This reasoning is very much in line with the skill-weights approach proposed by Lazear (2009), who argues that all skills are general and that it is their combination and the weights based on the demand for skills of individual firms that make these skills firm-specific.

What drives investment in training?

Measuring investment in training requires understanding the drivers and incentives that may lead both employers and employees to make such an investment.

Employees expect higher levels of education and skills to entail higher levels of earnings and, more generally, better jobs; a lower probability to get laid-off; and a higher likelihood to find employment after an unemployment spell and to get re-employed. There might also be non-monetary payoffs to investing in training, such as the prospect of obtaining a different job, entailing for example better working conditions, less travelling, less stressful activities, etc.. Existing empirical evidence supports such expectations, for both education and firm-specific training (e.g. Lynch, 1991). Dickson (2013), for instance, estimates that British male workers can expect around a 10% return to education for each additional year of schooling. Also, higher levels of education appear to positively correlate with on-the-job tenure, and with the probability to find a job and to get re-employed (e.g. Biagi and Lucifora, 2008; Riddell and Song, 2011; Núñez and Livanos, 2010).

Firms' expected payoffs from investment in human capital in the form of training are also important: increased productivity of the trained employees; fewer fluctuations in employment, and stronger bonding between employees and firms, thanks to the rewarding effect that training might have on the workforce. Positive and significant effects of both general and firm specific training on firms' productivity growth have been found in many studies (see de la Fuente and Ciccone, 2003, for a survey).

In what follows, the incentives to invest in the different types of training, for both firms and employees, are discussed in more detail, as well as the other factors that should be taken into account when trying to model and estimate investment in employees' training.

Employees' and employers' incentives to invest in training

Since Becker (1962), the literature on continuous education has been modelling and investigating the incentives of both employers and employees to invest in training, and the link between these incentives and the nature of the training provided, i.e. whether vocational or on-the-job versus general training.

From an employee perspective, it can be expected that training that is broad in scope and generic in nature (e.g. university degree) will benefit workers, in terms of e.g. higher wages and vertical mobility, in any company. Conversely, firm-specific training is likely to bring maximal payoffs if employees remain in the company providing or sponsoring the training. From an employer perspective, theory predicts that in perfectly competitive and frictionless labour markets employer-sponsored general employee training should not be observed. If firms behave rationally they should not pay for general training knowing that the likelihood of separation is very high, and employees might be able to find better (paid) jobs elsewhere. Hence, if general training takes place, it should be entirely employee-funded, for instance through lower wages during the training period. Firm-specific training, however, might be in theory co-sponsored, since both the employer and the employee might benefit from it. Employers might appropriate (at least part of) the returns from training by offering wages that are lower than the actual increased (marginal) productivity of workers. These wages, however, might still be higher in the company providing the training than in competing firms, thus benefitting employees as well (see Becker's Nobel lecture, 1993, for a discussion).

While the above theoretical prediction seem to only partially match what is observed in reality, theory and evidence on the source of funding for training gets reconciled if one discards the – not so realistic, in fact - assumption of perfect competition on the labour market.

Looking at the relationship between type of training and its financing, Lerman et al. and Riegg (2004) find that in 1994 and 1997 U.S. employer-funded training was mainly, although not exclusively, firm-specific, and that different data sources lead to different results. Other surveys e.g. Loewenstein and Spletzer (1999) and Booth and Bryan (2007), find that most job-related training is at least partially paid by employers, even when respondents view it as general. This is in line with Bassanini et al.'s (2007) analysis of European countries in the 1990s, based on the Continuous Vocational Training Survey, the European Community Household Panel, and the International Adult Literacy Survey (IALS).

Bassanini et al. (2007) further found that 71% of training courses in 1997 were directly paid by employers, independent of the nature of training, and that training did not translate into lower wages for the employees. They also noted that 80% of vocational training courses in 16 countries were paid by employers², and that on average, across all countries examined, less than 10% of the cost of employer-

2. It should be highlighted though IALS does not provide information on the possible decrease in employees' wages while training.

funded training was covered by the employee. Evidence that general training might increase the separation rate of employees in the two years following the training spell did not prove to be clear-cut, though.³

Interesting elements have also emerged from a number of studies linking investment in training to wage premia and labour market frictions.

Exploiting the 1996 wave of the European Community Household Survey for seven European countries, Bassanini and Brunello (2008) find that workers take up more training, especially outside the firm, if the wage premia of training are relatively less important.⁴ Conti (2005) also presents evidence of imperfect labour market mechanisms where the firm appropriates most of the returns to investment in human capital, while wages do not seem to be impacted by training. While theory predicts that the earnings elasticity of general training should be higher than that of specific training, Loewenstein and Spletzer (1999) for the United States, and more recently Jones et al. (2012) for Finland, find that general and specific training tend to have similar returns.

Finally, Brunello and Medio's (2001) model of labour market frictions and training fits the empirical evidence collected in Germany, Japan and the U.S. in the 1990s. They find that a more efficient matching of labour demand and supply reduces employers' propensity to finance training, as instead of training workers firms may simply search in the labour market and hire the skilled employees they need. Investment in training also appears as a decreasing function of greater unemployment, as the latter widens the pool of workers who can be hired at a relatively lower cost from the market.

Acemoglu and Pischke (1999a and 1999b) look at whether labour market frictions increase the propensity of employers to finance training, independent of the nature of training, by compressing the structure of wages. In particular, they suggest that imperfect matching in the labour market due to mobility costs, search frictions and preferences over employment that are not embodied in wages - such as location, work culture, and social content of the work - can increase employees' cost of switching companies. This in turn provides employers with some monopsony power on wage setting and providing training thus becomes profitable for the employer, who can appropriate the rents from a positive marginal productivity-wage gap triggered by training.

Another possible source of monopsony power is highlighted by Booth and Zoega (2008). Their model assumes that only high-skilled employees can perform complex tasks and can thus raise the average level of a firm's production complexity through spillovers to other colleagues. However, as only a few firms can perform under such complexity, they enjoy some monopsony power over the wages of high skilled employees, which in turn raises the returns on financing the general training of employees.

3. Brunello and Gambarotto (2007) and Brunello and De Paola (2008) look at the relation between training and agglomeration and find that in the '90s, in the UK and Italy respectively, firms in economically denser areas provided relatively less training, as agglomerations seemed to favour poaching of employees between firms. Kambourov et al. (2012) instead investigate the differences between government-sponsored and privately-sponsored continuous training. Among other results, they highlight that evidence linking government-sponsored (vs employer-sponsored) training to lower wages is actually reflecting a selection mechanism. Employees wanting to change occupation and that consequently perceive lower wages independently on training, self-select into government-sponsored training programmes. While very interesting indeed, these dimensions will not be addressed in the present study.

4. This is in contradiction with Becker's (1962) model, where workers would be keener to take general training only in presence of increasing wage premia.

The results discussed above are consistent with the models and empirical findings proposed by the literature linking investment in training to business cycles. In theory, training, and firm restructuring more generally, should be less frequent when opportunity costs in terms of foregone revenues from production are comparatively higher (Hall, 2000). This usually happens in times of economic booms, during which unemployment is also decreasing. In times of economic slack, on the contrary, it would be possible to see increases in investment in training. Yet investment in training should be expected to be pro-cyclical when considering the complementarity between technology and skills, as productivity-enhancing technical change should increase the rents that employers can extract from training. What is more, pro-cyclicity seems more likely when considering that investment in human capital cannot be posed as collateral, and that it must therefore be financed mainly through own-profits (Bassanini et al., 2007).

Evidence seems to mainly support the counter-cyclical hypothesis. Bassanini et al. (2007) find that greater unemployment and a more negative output gap increase the propensity to train in European countries, whether the training is employer-sponsored or not. Caponi et al. (2010) present similar evidence for Canada, but they also show that some pro-cyclicity exists in the best performing (i.e. least declining) sectors. Such findings support the predictions of the Mortensen-Pissarides-type of model proposed by Caponi et al. (2010), whereby the inflow of labour into the best performing (least declining) sectors decreases the productivity threshold above which employees need training to find a job. A greater number of employees would therefore ask for training.

Industry structure, firm characteristics, and training

Investment in training is likely to be affected also by industry structure and firm characteristics. Small firms may in fact face a relatively higher cost of employees training, as compared to their revenues. This can lead to lower payoffs from training in terms of productivity enhancements, as internal reallocation of trained employees and the adaptation of the production structure are less frequent. Moreover, smaller firms are usually more financially constrained, and this may limit their ability to invest in employee training and to increase the wages of their trained staff, to try and reduce their turnover. If trained employees are finally bidden away from the firm, smaller companies usually have a harder time replacing them than their larger counterparts.

Lerman et al. (2004) confirm that both the number of trained employees and the number of training hours per employee are lower in smaller firms in the U.S. according to data reported in the 1994 and 1997 waves of the Survey of Employer-Provided Training. Bassanini et al. (2007) find similar results for Europe and add that cross-country differences in the propensity to train can be related to the different company size distributions across country. Frazis et al. (2000) suggest that larger firms can offer and sponsor more training because they offer better employee benefits, which in turn increase employees' return to training in the providing company and reduce employee turnover.

Another element that relates to both firm size and the propensity to train is the level of competition in the industry. Everything else held constant, more competitive industries should display smaller average firm size, but also less training, if the rents generated by higher productivity after training are reduced because of competition (Acemoglu and Pischke 1999). But, increases in productivity due to greater competition in the product market could be so significant that the return to training would still be positive. This is especially true when competition stimulates innovation and technological change, which in turn requires upgrading the skills of the workforce, in order to be productive.

Finally, higher competition and lower firm survival decreases employees' chances to find better jobs in competing firms, and this decreases workers' bargaining power over wages (Bassanini et al., 2007). The complexity of these dynamics is reflected by the mixed empirical evidence arising out of those studies investigating the link between competition and training. Schone (2007) finds that greater competitive

pressure from foreign companies increases training in Norwegian manufacturing firms, whereas Picchio and van Ours (2011) do not find any significant relationship between training and product market competition or international integration. Finally, Bassanini and Brunello (2011) find a positive sign for the same relationship in 15 OECD countries. In their model, the decreasing effect of greater product market competition is more than compensated by the increase in the number of firms providing training.

Measuring training: an expenditure-based approach

Although the theory and evidence discussed above mainly refers to vocational and on-the-job training, taken together, these studies suggest that estimating investment in training would require considering, among others:

- investment made in the different types of training that may take place, i.e. formal training, vocational or on-the-job training, and informal learning;
- The funding of training expenditure by employers and employees;
- The return to investing in training for both employers and employees;
- When the training takes place, i.e. during or outside working hours;
- The characteristics of the company and the industry where training takes place.

The measurement strategy proposed in the present study takes stock of these insights and proposes a measurement approach that relies on some key assumptions.

First, firms are held to behave rationally: no firm would invest in training that would not be useful to its purposes, these being to increase its productivity or e.g. to reward employees in order to minimise separations and workforce turnover.

Second, and linked to the first point, a revealed preference approach is pursued whereby the fact that firms pay for at least part of the training and/or allows it to happen fully or partially during working hours is understood as a signal that the company deems the training useful or needed, and hence considers it as an investment. Also, the willingness of employees to enrol in training at their own expense – in terms of time and monetary cost – while actively in the workforce is understood as investment aimed at e.g. avoiding being dismissed or finding a better job, and is thus taken into account, even if companies do not pay for it.

Third, information about the perceived usefulness of training is used to discount investment in the different types of training for which such information is provided in PIAAC, as this is taken as an indication of the ‘real’ value of the training provided in terms of prospects for productivity increases for the company.

Fourth, investment in training is measured in terms of both the direct and opportunity costs of training. The opportunity cost of training is proxied by the forgone hours of work or leisure due to training. The direct cost of training is estimated using information about the repartition of the training costs between employers and workers. This accounting approach builds on the KBC measurement literature (OECD, 2013, for a review) and on O’Mahony (2012) and Corrado et al. (2014) in particular as far as investment in firm-based training is concerned and considers only part of training expenditure as productive investment.

Also, in this study the estimation of investment in training based on expenditure data takes into consideration that the cost of training might vary with firm size and that companies of different size might have different propensities to provide and sponsor training. Estimates further account for the private or

public nature of the companies and are provided for the private and the public sector (institutional entities or government-sponsored enterprises) separately.

As a general caveat, it should be noted that the methodology proposed in this paper implicitly assumes imperfect labour markets. While it estimates the opportunity cost of training based on reported individual wages, these are not assumed to reflect the marginal product of labour. While this does not represent a problem when constructing an expenditure-based measure of investment in training, it may nevertheless to some extent bias the analysis of the contribution of training as KBC to productivity growth.

Data sources: linking PIAAC to national data

As mentioned, the principal source for the present analysis is the PIAAC 2012 survey (see Annex 1, with respect to the exact wording of questions considered in the analysis). This survey allows assessing investment in different types of training while guaranteeing maximal international comparability, in terms of classifications used with respect to educational attainment (according to ISCED 2011), field of economic activity (by ISIC rev. 4) and occupation (by ISCO 2008).

PIAAC provides information about an individual's: employment status, i.e. whether employed, self-employed or none of the two; employment sector; type of occupation; wage; working hours; educational background; and current education or training activities, in terms of formal and on-the-job training and informal learning. All these pieces of information are provided in a way that makes them usable in quantitative analysis.

In order to estimate investment in training, however, it is also necessary to link PIAAC with other sources of information. This implies addressing a few challenges, which are described in Box 1.

Box 1. Combining PIAAC and external data sources

The first challenge implied by the use of external data sources together with PIAAC relates to the difference between the age distribution of the population targeted by the survey, which covers individuals aged 16 to 65, and that of Labour Force Surveys. The latter uses traditional 5 year age groups, and reports single data points for the 15-19 year olds and for the 65-69 year olds. In order to use information from LFSs for individuals of age 16-19 or 65 only, this study uses data from national Censuses to compute the average share of 16-19 year-old in the whole 15-19 age group and the average share of 65 year-old in the whole 65-69 age group.

A second challenge arises from the fact that in three instances the target population for the survey design differs from a country's total population. This is the case of Belgium, where only Flanders are part of the survey; the United Kingdom, where data only relate to England and North Ireland; and Russia, where the Moscow region is excluded from the survey. The system of weights constructed in this survey corrects for the first two issues, but not for the third one.

A final difficulty arises from the fact that the PIAAC survey took place over a two year period, i.e. in 2011-2012 (only in the case of France the survey was fully implemented in 2012). The user who needs to link PIAAC to external data sources is thus required to make a judgment call about the year of external data that can be associated to the information reported in PIAAC.

Also, adjusting the survey weights to account for the population not included in the PIAAC sample and aligning the structure of employment arising from PIAAC to the one emerging from official sources implied taking a number of steps. Data about age by gender, employment status, economic sector and occupation were taken from EU LFS for EU countries and from the Current Population Survey (CPS) for the United States and from the Economically Active Population Survey (EAPS) for Korea. For the sake of brevity, these data sources are collectively referred to as LFS. LFS-type data have the advantage of relying on bigger survey samples than PIAAC and to provide data for all relevant countries.

The OECD statistical database² provided all LFS relevant data for all EU countries plus Japan and Korea, as well as information about occupations by economic sector and the proportion of full time and part time employees. For the other non-EU OECD member states included in the analysis, gathering information about the structure of the economy and the industry-specific distribution of occupation in an internationally comparable fashion posed some additional challenges. These data are in fact available only following national classifications that are different from the ones reported in PIAAC, namely: ANZSCO (Australian and New Zealand Standard Classification of Occupations), NOC

(National Occupational Classification) and SOC (Standardized Occupational Classification) for occupations; and ANZSIC (Australian and New Zealand Standard Industrial Classification) and NAICS (North American Industry Classification System) for economic activities. Shares of employment by the ISIC rev. 4 classification of economic activities for Australia, Canada and United States are thus based on OECD calculations³.

Employment by occupation for non-EU member states was obtained from three different sources. Data for Australia, Japan and Korea at one digit ISCO 2008 level were obtained from the International Labour Organization statistics ILOSTAT.⁴ Similarly, data for Canada at one digit ISCO 2008 level were obtained from the United Nations statistics UNSTATS.⁵

In the absence of a data source providing U.S. employment by occupation data following the ISCO 2008 classification, a crosswalk was built between CPS, where occupations are classified following the Census 2010 occupation codes, and PIAAC, where occupations are classified according to the ISCO 2008 classification.⁶ To this end, we first re-classified Census information in SOC 2010 categories using the existing crosswalk between Census 2010 and SOC 2010 classifications, and then associate the SOC 2010 classification to the ISCO 2008 one, for which a conversion table is also available. In the occurrence of one-to-many correspondences between Census 2010 and SOC 2010, data are disaggregated using SOC employment-based weights. Once CPS employment data are classified according to SOC, the crosswalk between SOC and ISCO is used to finalise the conversion. This exploits population weights based on the CPS employment as newly classified in SOC 2010 categories.

Finally, recalibrating the PIAAC-provided weights, as explained before, requires using data from the System of National Accounts (SNA). However, SNA information on wages and salaries by ISIC rev.4 sectors alone would not suffice, as SNA labour market structure data only account for the wages and salaries of employees, thus overlooking the corresponding figures for self-employed individuals. As the latter are an essential part of the workforce and are surveyed in PIAAC, adjustment coefficients by country and industry have been calculated based on the following criterion:

$$COEF_{c,j} = \frac{Employees_{c,j} + Selfemployed_{c,j}}{Employees_{c,j}} * Wages_{c,j}$$

where $COEF_{c,j}$ is the resulting adjustment coefficient by country c and industry j , $Employees_{c,j}$ is the number of employees obtained from LFS; $Selfemployed_{c,j}$ is the number of the self-employed population from LFS; and $Wages_{c,j}$ are gross wages and salaries from SNA⁷. The implicit assumption made here is that, other things held constant, the wages of the self-employed do not substantially differ from those of corresponding employees (see Freeman, 2011, for a discussion).

For Japan and Korea, however, SNA data on wages and salaries by ISIC rev. 4 are not available, contrary to total compensations of employees and the ratio between total compensations and total wages and salaries by ISIC rev. 4. As a consequence, yearly wages and salaries by ISIC rev. 4 were approximated multiplying such ratio by the total compensations of employees.

Notes:

¹ In light of the difficulty to construct representative weights excluding the Moscow region, and to exploit appropriate conversion tables for occupations and sectors, the Russian Federation was excluded from this analysis.

² Available online at: <http://dotstat.oecd.org>

³ see http://10.101.26.220/data_lfs_sources.html

⁴ Available online at: <http://www.ilo.org/ilostat/>

⁵ Available online at: <http://unstats.un.org/unsd>

⁶ No direct official crosswalk exists between the Census 2010 and the ISCO 2008-based PIAAC classification.

⁷ OECD National accounts statistics, Available online at: <http://dotstat.oecd.org>

Estimating investment in training in a way that would be representative at the country and industry level requires constructing a new set of weights for the individuals in the PIAAC survey. Such a need becomes evident upon comparing the employment figures of the full PIAAC sample with those obtained from LFS for the 15 EU countries included in the survey in the age group 24-49 -with the 15 countries and age groups chosen as they allow for a straightforward comparison between PIAAC and LFS.⁵

5. Belgium and the United Kingdom are omitted from the comparison as the PIAAC target population of Belgium consists only of Flanders, and the UK ones only of England and North Ireland.

Table A1 in Annex 2 shows in grey the countries where differences between PIAAC and LFS employment figures exceed 5%. The many differences that emerge suggest that combining PIAAC data with other data sources – with the latter mainly provided at the country level only – requires adjusting sample weights. This becomes even more evident when comparing the within-country industry-specific distribution of employment across data sources. For instance, in Finland, a country for which aggregate employment based on PIAAC and LFS looks basically the same, remarkable differences exist when comparing industry-specific employment figures (see Table A2). Differences appear especially pronounced in sectors (in grey) such as: electricity, gas, steam and air conditioning supply; financial and insurance activities; and real estate activities.

Final estimates were further refined by winsorising the distribution of the key input variables at the 1% and 99% values, thus limiting the role of possible outliers and the measurement error triggered by extremes values. In particular, wages were corrected taking into account industry-specific distribution, while employment per hour was corrected with respect to the occupation-specific distributions.

The final calculation of set of weights making PIAAC-based statistics representative for the entire population of countries follow Deville and Särndal (1992) and the subsequent literature (e.g. 2013b). Weights are obtained through the generalised regression estimator (GREG), which uses the link between survey information and out-of-survey auxiliary variables to adjust the sampling weights.⁶

Measuring training: a PIAAC-based methodology

The methodology proposed for the estimation of investment in workforce training addresses a number of the issues raised by the literature, also thanks to new and rich individual-level information collected through the OECD PIAAC survey. The estimates proposed encompass investment in three forms of training, namely formal and on-the-job training and informal learning, and thus improve on existing work which typically overlooks formal training and informal learning. They cover 22 OECD countries, at the economy-wide and the industry levels and, contrary to existing estimates, the proposed figures rely on data collected via the same survey, which uses harmonised definitions of the types of training considered. They further account for both the opportunity and the direct cost of each form of training, similarly to the approach used by O'Mahony (2012) when estimating on-the-job training.

Investment in “formal training”, “on-the-job training” and “informal learning”

Addressing a shortcoming of existing studies, the present analysis proposes a methodology for the measurement of investment in formal training, on-the-job training and informal learning. The inclusion of formal training aims at capturing general investment in human capital, and encompasses training related and unrelated to the current occupation of individuals.⁷ In times of excess labour supply, high unemployment rates (also occupation-specific) and relative higher job uncertainty, workers may well have incentives to invest in their skills and education, and to do so even at their own expense and not necessarily in relation to their current job requirements. Investing in formal training may in fact lower their probability to become or remain unemployed, raise the likelihood of finding a (suitable or better) job – also in different industries – and improve vertical mobility. In this respect, Kambourov and Manovskii (2004) for instance

6. This study exploits the following auxiliary variables. For the entire population: age, gender, economic status (employed, unemployed, inactive); for the employed population: economic sector, occupation, total wages and salaries by industry, employment in working hours.

7. The PIAAC survey provides information about the usefulness of training for the current job. See later sections.

report occupational mobility across industries to have been larger than that across occupations in the U.S. between 1968 and 1993.⁸

Existing studies only very seldom incorporate measures of informal learning; they rely on heterogeneous data collection and estimation methods; and time- and country-specific information availability vary widely. Omitting to account for informal learning may artificially increase the return to formal and on-the-job training, as evidence suggests that the three forms of training are highly complementary. Engaging more in formal and on-the-job training may in fact increase employees' participation in informal learning as well, enhance their absorptive capacity and increase the prospect returns of investing in such training (e.g. Borghans et al., 2006).⁹

Total investment I in training can be defined as the sum of the three components:

$$I = I^F + I^N + I^{IN} \quad (1)$$

Where I^F is investment in formal training, I^N investment in on-the-job training, and I^{IN} investment in informal learning.¹⁰ The following sections describe the assumptions made and the analytical steps proposed to estimate each of these components based on PIAAC individual level information for 2011-2012. The goal is to estimate I at the country and industry level, although for some of these components occupation-specific estimates can also be proposed. As the returns to training are linked to the degree of generality or specificity of the formation received, and this may in turn relate to both industry- and occupation-specific aspects, estimating investment in training at both the occupation and industry level may provide interesting insights. The present paper, however, only presents the estimates at the industry level, so as to enhance comparison with existing literature.

Direct and opportunity costs of training

As anticipated, a noteworthy feature of this study is the inclusion of both the direct and opportunity costs of training in the proposed measure of expenditures in training. The opportunity cost of training is estimated in terms of forgone hours of work due to training. While this information is not explicitly contained in PIAAC, the survey provides data related to the allocation of training between working and leisure hours, and to the usefulness of training to the worker's current employment, which can be used to proxy the opportunity cost of training. As far as the direct cost of training is concerned, an estimate of the repartition of the training costs between employer and worker will be needed, as discussed later.

Surveyed individuals in PIAAC are asked to report whether training took place "only during working hours", "only outside working hours", or somewhere in between, out of four possibilities (see the "Allocation" variable).¹¹ If firms behave rationally and labour markets are competitive, employers might

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8. This in turn will result in different degrees of depreciation for the resulting capital stock of training when the latter is estimated at the industry or occupational level, since depreciation of human capital is linked to the employee's mobility.
 9. Informal learning to some extent sets itself apart from formal and on-the-job training since it lacks structure and organisation. These features can in principle support the alternative choice not to include informal learning and training in the analysis.
 10. Equation (1) implies that 100% of expenditure in the three forms of training as from the algorithms described below are considered investment. However, I^F , I^N and I^I are themselves the result of an estimation for which only a fraction of the cost of training is considered investment. This corresponds in Corrado et al. (2009) and Corrado et al. (2012) to a capitalisation factor of less than 1.
 11. For the precise wording of the relevant questions, please refer to Annex 1.

allow training to take place during working hours if and only if workers' productivity is expected to increase at least as much as the cost incurred in terms of foregone working hours due to training. However, when labour markets are not perfectly competitive or when employees' outside options are (relatively) fewer because of excess labour supply and consequently high unemployment rates, employers may be able to (at least partially) shift the time and cost of training onto employees, while still benefitting from the productivity returns driven by training. This reasoning drives the choice made in the present study to consider also training happening outside working hours as investment in training.

In PIAAC, information about the time in which training takes place is complemented by information on the employees' perceived usefulness of the learning activity for their current job. Answers are reported on a four-step scale, ranging between "very useful" and "not useful at all" ("*Subjective Usefulness*").

Consistent with the expenditure-based approach used in KBC-related studies as Corrado et al. (2005), the present study looks at expenditures from the employers' perspective. Hence, expenditure in training configures itself as investment the more workers report it to be useful for their current jobs, and the more training happens during working hours, as it is assumed that training can happen during working hours only if it is a rentable investment for the company. This latter occurrence can be considered a revealed preference of the employers, and of the expectations they have about the usefulness of their employees' training. However, relying on the "*Subjective Usefulness*" question only is not sufficient to capture the proportion of expenditure that should be considered as investment. PIAAC asks employees rather than employers to assess the usefulness of their training, and relying only on the subjective usefulness assessment of employees might lead to overlook training considered as irrelevant by the employee but of value to the employer.

To make the "*Subjective Usefulness*" and "*Allocation*"-related answers usable for estimation purposes, an order based on the semantic understanding of their meaning is imposed on the answers. This has been translated into values bounded between 0 and 1, and used as a capitalisation factor of the expenditure in training. Given the impossibility to compare the precise meaning of "moderately" and "somewhat" relative to "very" or "not at all" (likewise for "mostly during" and "mostly outside" working hours), the two intermediate answers of each question have been attributed values that are equidistant between 0, 1 and between each other, i.e. 0.33 and 0.66 (see Table 1). This arguably logical and straightforward choice nevertheless relies on the implicit assumption that respondents see the possible answers as equidistant from each other, rather than seeing, e.g. 'mostly during working hours' closer to "only during working hours" than to "mostly outside working hours".¹² The values of "*Allocation*" are increasing in the proportion of training happening during working hours, coherent with the idea that training happening during working hours is more likely to be rentable for the employer, therefore a more rentable investment.

The variable p summarises the joint answers to the "*Allocation*" and "*Subjective Usefulness*" questions, by taking the average of the values attributed to the answers to each question.¹³ For example, an individual answering that the training took place mostly during working hours (0.667) and that the training was very useful (1) will be attributed a value of p equal to $(0.667+1)/2$, or 0.833. Table 2 shows the values of p resulting from all possible answers to the two PIAAC questions considered.

12. Following this reasoning, an alternative weighting strategy may for instance assign the following values to the different answers: 1; 0.75, 0.25; 0. This is implemented as a robustness check in a later section.

13. As p is computed for each individual answering to "*Subjective Usefulness*" and "*Allocation*", it has an individual, occupational, industrial, and country-specific dimension. In the interest of simplicity, the indexes referring to these dimensions are omitted in this section. This applies to q^s here below, too.

Table 1. Answers and assigned numerical values to “Allocation” and “Subjective Usefulness”

Allocation	Attributed Value
Only during working hours	1
Mostly during working hours	0.667
Mostly outside working hours	0.333
Only outside working hours	0
Subjective Usefulness	Attributed Value
Very useful	1
Moderately useful	0.667
Somewhat useful	0.333
Not useful at all	0

Source: Authors' own compilation on data from the PIAAC survey

Table 2. Values of p

Allocation →	1	0.667	0.333	0
Subjective Usefulness ↓				
1	1	0.833	0.667	0.5
0.667	0.833	0.667	0.5	0.333
0.333	0.667	0.5	0.333	0.167
0	0.5	0.333	0.167	0

Source: Authors' own compilation.

An alternative way to derive a variable representing the joint distribution of “*Subjective Usefulness*” and “*Allocation*” would be to multiply the row and column values. This would, however, have the undesirable property of setting p to zero whenever one of the two underlying variables is zero. As mentioned, it is reasonable to suppose that training efforts taking place during working hours signal an interest of the employers, even when employees perceive them as useless and that training taking place completely outside working hours can be very useful for the company as well. This is especially true if the cost of training can be shifted to the employee in the presence of labour market imperfections or unfavourable labour market conditions.¹⁴

A final difference with respect to previous methodologies and in particular to O’Mahony’s (2012), lies in the estimation of the direct cost of training. While O’Mahony (2012), in light of data restrictions,

14. The values of p computed as a simple average are always higher than the values that would result from multiplying the two variables considered, whenever the values of “*Subjective Usefulness*” and “*Allocation*” are less or equal to one. Defining p as the product of values for “*Allocation*” and “*Subjective Usefulness*” is in fact possible without losing information scale values that exclude the zero are attributed. One possible such strategy would imply attributing values e.g. from 1 to 4 (similar to a Lickert scale) to the answers to both questions, and then normalising the product of the answers to constrain p between 0 and 1. This is done in a later part of this paper, as a robustness check.

assumes that whenever training takes place outside working hours its cost is entirely borne by the employee, PIAAC registers whether the employer pays for at least part of the training (“*Employer’s Quota*”). More precisely, PIAAC provides information about the employer paying for the totality, a part, or none of the costs of training, and further informs about the existence of such costs. Table 3 shows the value attributed to the “*Employer’s Quota*” answer, based on the assumption that the greater employers’ participation in the cost of training is, the more likely that this expenditure is seen as investment. The implicit assumption made here is that the value of training does not correspond only to what the employer pays, as other firms might ultimately benefit from this training when employees move across firms, between and across industries.

Table 3. “Employer’s Quotas” possible answers and assigned numerical values.

Employer’s Quota	Attributed Value
Yes, totally	1
Yes, partly	0.5
No, not at all	0
There were no such costs	0

Source: Authors’ own compilation on data from the PIAAC survey

From the joint answers to “*Employer’s Quota*” and “*Subjective Usefulness*” a new variable, q , is derived. Similar to what is done above, employers’ participation in the costs of training is understood as signalling an interest of the employers in the training of employees, even if the training is considered useless by the employee. Symmetrically, training which is not paid by the employer in any proportion need not necessarily be irrelevant for the job tasks. Table 4 reports the values of q as an average of the possible answers to the two original PIAAC questions.

Table 4. Values of q

Employer’s Quota →	1	0.5	0
Subjective Usefulness ↓			
1	1	0.75	0.5
0.667	0.833	0.583	0.333
0.333	0.667	0.417	0.167
0	0.5	0.25	0

Source: Authors’ own compilation

Questions on “*Allocation*”, “*Subjective Usefulness*” and “*Employer’s Quota*” are asked twice in PIAAC, once in reference to formal training, and once in reference to on-the-job training.

Formal training

The definition of formal training used in this study corresponds to formal education in PIAAC, i.e. the highest level of schooling the interviewed employee reports to have attended in the last 12 months.¹⁵ It

15. Although PIAAC surveys also unemployed people, this analysis is restricted to individuals in employment at the moment of the interview, in order to provide a relevant, industry- or occupation-specific estimate of investment in training. The terms “individual” and “employee” are therefore used interchangeably.

therefore refers to formal education provided by schools, universities or other education institutions, full- or part-time, which lead to a certification reported in the National Educational Classification.¹⁶

Investment in formal training I^F in a given country and year is estimated as a sum over individual information in each occupation and sector, according to equation (2):¹⁷

$$I^F = \sum_{k,o,j} (p_{k,o,j} h_{k,o,j} w_{k,o,j}) + \sum_{k,e,o,j} (q_{k,e,o,j}) \frac{C_e}{S_e} \quad (2)$$

where $p_{k,o,j}$ and $q_{k,e,o,j}$ are the individual-specific weights discussed before, and “Allocation”, “Subjective Usefulness” and “Employer’s Quota” refer to formal education.¹⁸ They are derived for an individual k :

- working in occupation o , defined according to the 2008 International Standard Classification of Occupations (ISCO 2008) at the 4 digit level;
- in industry j , defined according to the most recent revision of the International Standard Industrial Classification of All Economic Activities (ISIC 4), at the 4 digit level;
- attending education e , defined according to a modified version of the one digit International Standard Classification of Education (ISCED 1997);
- h corresponds to the annual hours worked by the individual;
- w to her gross hourly income¹⁹; and
- C_e/S_e is the yearly public and private expenditure in education per student for the year 2011, as reported in the OECD “Education at a Glance” statistics and converted from purchasing power standards (PPS) to national currency using the OECD PPS for 2011.²⁰
- and S_e is the number of students attending formal education.

The first part of the right hand side of equation (2) reflects the opportunity cost of formal training. When training takes place during working hours, the opportunity cost for employers is represented by the hours of work that the employee cannot input in the production process due to the training. The higher the proportion of training performed outside working hours, the lower the opportunity cost for the firm. However, workforce training may represent an investment for firms even when the training activity takes place entirely outside working hours (“Allocation” equals zero), as long as the training has some usefulness, i.e. it can be then be exploited in the production process (“Subjective usefulness” different from zero). The opportunity cost of formal training is thus computed as the corresponding proportion of an

16. Thereby excluding other certificates of training of a less formal nature.

17. The subscripts for country and time are omitted to ease notation. To obtain industry-specific measures, one should amend equation (2) and sum over all individuals in different occupations within the same industry; for an occupation-specific measure, one should only sum over all individuals in different industries within the same occupation.

18. $p_{k,o,j}$ and $q_{k,e,o,j}$ for formal training for Japan in sector J are missing, as no answer has been provided to the underlying questions by all PIAAC respondents working in the sector. To address this shortcoming the answers from Korean respondents in the same four digit sector were used instead.

19. Hours worked are not censored to 60 per week. Monthly wages for individuals who did not report any income are estimated with the aid of a country-specific Mincer-like equation where the individual’s wage is a function of her level of schooling (6 categories), age (5 categories), gender, industry (21 categories), occupation (11 categories) and country of operation.

20. In practice, the classification in the OECD “Education at a Glance” is more aggregate than the one in PIAAC, although always based on ISCED1997. Aggregate categories in PIAAC are then created so as to match those for which information on education expenditure is available.

employee's annual wage bill ($h_{k,o,j} w_{k,o,j}$) multiplied by a weight that takes into account the repartition of training between working and non-working hours, and the perceived utility of training, i.e. p .

Holding that “Allocation”, and hence p , should be able to capture whether an employee is or is not enrolled in full-time education, the proposed indicator for formal training is based on a proportion of the annual wage bill of the employee, as if the employee was spending her entire working time in education. Data restrictions influence this choice: PIAAC does not ask the number of hours invested in formal training, contrary to other forms of training, so that h cannot be the number of hours of formal training (as it happens instead with on-the-job training, as discussed in the next section).²¹

The second part of equation (2) approximates the direct cost of formal education based on the per-student expenditure in the level of education attended by the individual (C_e/S_e). This ratio is then multiplied by q , a variable weighting expenditure in education by the perceived usefulness of training, and the quota of training costs paid by the employer. If one were to ignore q , the sum of the per-student expenditure over all interviewed individuals in PIAAC might become greater than the total country-wide expenditure on education, if the number of students is smaller than the number of employees. This should not represent a problem if the number of employees in formal training is included in the national education statistics (as it should be).

On-the-job training

On-the-job training in PIAAC encompasses different forms of training ranging from seminars and workshops, to on-the-job training periods, extra courses or private lessons, and open or distance education courses. They are usually planned and organised in nature, but not in the context of a formal education degree; they might but need not take place at work, nor be exclusively relevant for a specific firm.

On-the-job training I^N is defined here as:

$$I^N = \sum_{k,o,j} (p_{k,o,j} h_{k,o,j}^N w_{k,o,j} + q_{k,o,j} h_{k,o,j}^N C_j^N) = \sum_{k,o,j} h_{k,o,j}^N (p_{k,o,j} w_{k,o,j} + q_{k,o,j} C_j^N) \quad (3)$$

where h^N is the number of hours invested in on-the-job training in a year reported by the employee, and $p_{k,o,j}$ and $q_{k,o,j}$ are calculated as described above, but when questions on “Allocation”, “Subjective Usefulness” and “Employer's Quota” refer to on-the-job training. C_j stands for the average cost of an hour of training in the industry and firm size class.²²

The first part of Equation (3) ($p_{k,o,j} h_{k,o,j}^N w_{k,o,j}$) accounts for the opportunity cost of on-the-job training, following the same line of reasoning as above. The number of hours worked are here substituted

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21. Part of the hours worked are not translated in investment thanks to the “discount factor” p , which considers the proportion of hours of training which take place during working hours. However, if formal training reduces the number of reported working hours, the researcher cannot easily quantify how these hours translate into investment in training. The present methodology implicitly assumes that these hours (where *Allocation* equals 0) can be estimated as a proportion of actual worked hours described by the *Subjective Usefulness*. This is in principle fine, as the first component of Eq.2 should represent the opportunity cost of the firms in providing training, and it cannot therefore be based entirely on the number of hours the worker spends on training outside the firm boundaries.
22. Due to restrictions in the data availability, the level of industry aggregation of C_j can be different from that of the other components of investment in non-formal training. Refer to Box 1 for further information.

by the number of hours effectively spent on training, as reported in PIAAC. The second part of Equation (3) conversely computes the individual's direct cost of on-the-job training ($q_{k,o,j} C_j^N h_{k,o,j}^N$), as a weighted product between the cost of one hour of on-the-job training and the number of hours invested in such activity.

The weighting follows the intuition described for formal training, so that costs are capitalised into investment in function of the perceived usefulness of the training and the participation of the employer to its costs (“*Subjective Usefulness*” and “*Employer’s Quota*”). A note of caution, however, is appropriate: as the average cost C_j^N is obtained from firm-level surveys, the present estimates of the direct cost of training may be subject to a bias of unknown sign, as discussed in more details in Box 2. C_j^N takes into account both the firm’s own cost of training and the fee paid to external training companies for their services, thanks to information available in the Continuing Vocational Training Survey, the dataset used to estimate the direct cost of training.²³ C_j^N excludes the training subsidies received by the company, so that only the actual expenses incurred by the company are considered when estimating investment in training.²⁴

Box 2. The direct cost of on-the-job training

The direct cost of on-the-job training for an individual is estimated based on C_j^N , the cost of an hour of training in the industry. This information is obtained from the Continuing Vocational Training Survey (CVTS) collected from European firms. In absence of similar recent sources containing information about the hourly cost of training for non-European OECD countries, information from the CVTS is also used to estimate the cost of on-the-job training for non-European countries, as explained below.

Before delving into details about how CVTS data are used, it is useful to highlight some features of these data and the possible estimation biases that they might trigger, and then discuss the way in which the present analysis tries to address them.

The CVT survey is addressed only to firms with 10 or more employees, and the latter may face different hourly costs of training compared to their smaller counterparts. Differences might also exist between relatively smaller and larger firms in terms of skill composition, degree of flexibility in employees’ occupational profiles, or degree of exposure to new technologies. This in turn would impact on the frequency, extent and quality of their training. Also, due to less bargaining power, smaller firms may need to pay more per unit of training relative to bigger companies. The methodology used to construct an appropriate cost measure for firms employing less than 10 employees is reported below.

The CVT survey includes information on firm-level spending for training only. The resulting measure of direct cost of training may therefore represent a lower bound cost indicator, as it excludes the direct cost of training borne by the employee. This partly compensates the fact that in Equation (3) this hourly cost is multiplied by the number of hours of on-the-job training as reported in PIAAC, where the number of hours includes time for both on-the-job training and seminars and distance courses; the cost of the latter, however, may be borne by the employee only.

The CVT survey excludes the cost of courses attended by trainees and apprentices, as in the case of the CVT survey for European countries. As far as apprentices in PIAAC report receiving on-the-job training (0.2 percent of total considered employment), their contribution to investment may be to some extent overestimated, if one believes that

23. For comparison, O’Mahony (2012) estimates investment in training as:

$$\left(\frac{\text{Direct cost of training}}{\text{Opportunity cost of training}} \right) * (\text{avg compensation (EUKLEMS)}) + \left(\frac{\text{Number trained employees by type \& industry}}{\text{total number employees by type \& industry}} \right) * (\text{wage by type \& industry}).$$

24. It cannot be excluded that training subsidies (or tax credits) influence firms’ training-related decisions on both the intensive and the extensive margin (i.e. how many hours per individual and how many individuals to train), the “employer’s quota” and the allocation of the training activity during working hours - hence both the direct cost and the opportunity cost of training. This methodology takes such firm’s decisions as given, and estimates investment as a consequence, and the proposed estimates should not be invalidated by the absence of information on the firm’s decisions on training were the subsidies not be in place.

their cost as well as their contribution to production is lower than other trained individuals. Also, the definition of on-the-job training in the CVTS might not perfectly overlap with the definition of on-the-job training used in the present study.

The coexistence of these three features makes it hard to forecast the direction (upward or downward) of the bias that the proposed estimation strategy might impose on the direct cost of on-the-job training.

On-the-job training in EU countries

For EU countries this study uses data collected by Eurostat in the last round of the CVTS (CVT4) survey. The survey offers the firm-specific cost of CVT courses and the number of training hours provided, with courses that can take place either within or outside firms' boundaries, and can be provided either by internal or external instructors. C_j^N is then calculated as the industry-wide average of firms'-specific ratios between the total cost of training borne by the employer and the number of hours of training.

Industry breakdowns are limited to the following industry aggregates of the Statistical Classification of Economic Activities in the European Community (NACE rev. 2): B-E (Industry except Construction); F (Construction); G-I (Trade, Transport, Accommodation and Food Services); J-K (Information and Communication, Financial and Insurance Activities); L-N+R+S (Real Estate, Professional Activities, Administrative Services, and Entertainment). For the remaining services (O-U, or public administration, education, healthcare, activities by international organisations and households), this study uses an average of the cost of all other services (F-N, R and S), in a similar fashion to O'Mahony (2012). Using conversion tables from NACE revision 2 to ISIC revision 4, it is straightforward to attribute the average cost from the CVT survey to the corresponding sub-industry in PIAAC.

A further adjustment to C_j^N takes into account the size of the firm in which the individual in PIAAC reports to have worked when in training. The CVTS contains information on the size of the surveyed company by broad classes (10 to 49, 50 to 249, 250 employees or more). It is therefore possible to calculate C_j^N not only by industry but by class size as well, and to attribute the appropriate industry-class average hourly cost of training to each individual in PIAAC. For PIAAC individuals reporting to have worked in firms smaller than 10 employees, this study uses the average direct cost reported by firms operating in the same sector in the class size 10-49. The implicit assumption made here is that the direct cost of on-the-job training is the same for all firms employing less than 50 employees operating in the same industry.

In the future, the robustness of the on-the-job estimates proposed may be tested by means of taking the ratio of direct to opportunity cost for PIAAC surveyed individuals working in company of 10 to 49 employees. The average of such ratios across all individuals in the same industry and class will then have to be multiplied by the industry-average opportunity cost of on-the-job training (as calculated in the first term of Equation 3) for workers in firms with less than 10 employees. Doing so would entail assuming that the relative importance of direct vs opportunity cost of on-the-job training is the same for all firms employing less than 50 employees in the same industry, rather than the actual average direct cost, as done in the current version of the methodology.

On-the-job training in non-EU countries

In the absence of data sources providing information about the country-specific cost of on-the-job training for *Australia, Canada, Korea, Japan, the U.S. and Ireland* (for which the latest CVTS information is 2005), estimates have been obtained as follows. All countries in the sample have been clustered on the basis of multiple PIAAC-based features of relevance for firm-level training, and of information from other datasets reflecting occupation and industrial structure-related features of the countries. A list of the variables used for the clustering is reported in part 6 of Annex 2. When clusters include both European countries and at least one country for which no training cost information is available, the average industry cost reported by the European countries in the cluster is taken as a proxy for the non-European country in the same cluster. This is done at the industry level, for the sake of accuracy. The country groupings resulting from the clustering are chosen according to the Duda and Hart criterion (Duda, Hart, and Storck, 2001) and reported in Annex 2, Table A7.

As an alternative, a different approach can also be implemented, which mimics what done in the case of micro firms. The ratio of direct to opportunity cost of on-the-job training computed for each PIAAC individual employed in a European company can be averaged by industry (and country), and the average of such ratios across countries can then be multiplied by the industry-averaged opportunity cost of on-the-job training (as calculated in the first term of Equation 3) for a worker in a non-European firm. This would yield industry-specific direct costs of training. This methodology, while appropriate in the case of low variability across countries, cannot be pursued in the present work, as suggested by the data shown in part 3 of Annex 2.

Informal learning

The last component of Equation (1) accounts for investment in informal learning. As, by definition, this form of training is neither structured nor organised, it is not possible to identify a direct and explicit cost of informal learning. Such a training component is therefore estimated as a function of the opportunity cost of the employee's lower output during the hours of training and the opportunity cost of other workers who may be involved in the training. The informal nature of this type of training also implies that it is difficult to identify what qualifies training as informal.

In this paper, the opportunity cost of informal learning is believed to be a positive function of:

- the frequency of learning from co-workers or supervisors ("*Peer Learning*");
- the frequency of learning-by-doing, i.e. while processing the daily job tasks ("*Learning-by-Doing*");
- the frequency with which an employee keeps up to date with novelties in the product market ("*Knowledge Updating*").

PIAAC contains information on all three aspects, and such information is used to propose conservative lower and upper bound estimates of the *number of days* spent in informal learning per year. This will then serve as an input for the quantification of the investment in informal learning.

PIAAC asks whether each of the "*Peer Learning*", "*Learning-by-Doing*" and "*Knowledge Updating*" activities takes place less than every day, at least once a week, less than once a week, less than once a month, or not at all. These categories are transformed into numbers by assigning the lowest possible amount of working days implied by the categorisation. For instance, if an individual reports to have engaged in one of the three activities above "less than once per month", it is assumed that the individual devoted exactly one working day per year to that specific activity. This is a very conservative approach, because "less than once a month" can imply significantly more than one occurrence per year. Nevertheless, absent a more precise definition of the frequency of the activities above, and in an effort to avoid overstating the importance and cost of training, the outlined approach is here preferred.

Table 5 shows the number of working days per year associated to each possible answer to the questions about "*Peer Learning*" (d^p), "*Learning-by-Doing*" (d^d), and "*Knowledge Updating*" (d^u). The number of working days when the individual is learning from its peers or supervisors is doubled so as to take into account the opportunity cost of the peers who are investing their own time as well in the informal learning activity.

This yields a relatively conservative estimate of the time spent in informal learning. Indeed, by considering that one hour of "*Peer Learning*" for the individual is costing one extra hour of its peers' and supervisors' time, the cost of informal learning may be underestimated. In particular, one hour of a supervisor's time should cost more than an hour of the employee's time. What is more, employees may be learning from more than one peer or supervisor at a time. The factor multiplying the number of hours invested by the interviewed employee in informal learning through "*Peer Learning*" could therefore be higher than two. On the other hand, whenever "*Peer Learning*" benefits more than one individual at the same time, the opportunity cost of the peers or supervisors which are "teaching" may be double counted, if "*Peer Learning*" is reported by all learning individuals at the same time. Unfortunately, no elements are available in order to understand if all these effects are biasing the estimation of hours of informal learning univocally, and the direction of the bias, i.e. whether upwards or downwards.

Table 5. Possible answers to the questions on “Peer Learning”, “Learning-by-Doing” and “Knowledge Updating”, and corresponding assigned working days.

Frequency of occurrence	Attributed Days per Year	
	d^d, d^u	d^p
Never	0	0
Less than once a month	1	2
Less than once a week but at least once a month	12	24
At least once a week but not every day	52	104
Every day	252	504

Source: Authors' own compilation on data from PIAAC. Legend: d^d and d^u are, respectively, the days associated to each reported frequency when the question refers to “Learning by Doing” and “Knowledge Updating”. d^p is the same but when the activity is “Peer Learning”.

A variable reflecting the number of working days actually devoted to informal learning in a year is then constructed. This corresponds to the sum of working days invested in each of the three activities considered, namely “Peer Learning”, “Learning-by-Doing” and “Knowledge Updating”, as derived in Table 5. In other words:

$$\bar{d}_{k,o,j} = d^d + d^u + d^p \quad (4a)$$

where any of the three frequencies can be zero, and the subscript of $\bar{d}_{k,o,j}$ reminds that these number of days is reported by an individual employed in a specific occupation and industry.

It should be noted, however, that one cannot assume these three activities to be mutually exclusive. An employee can be “learning by doing”, as much as “updating his knowledge about new products”, while interacting with peers and supervisors, for instance.²⁵ That is why taking the sum of the frequencies of all activities together as in Equation (4a) may lead to double counting some days, especially when the same individual reports to be involved in more than one of the informal learning activities considered. Moreover, it can be argued that the time spent in “Learning by Doing” and “Updating knowledge” (d^u and d^d) cannot be considered informal learning, as it might not entail a clear opportunity cost in terms of foregone hours or productivity of the employee. It follows that $\bar{d}_{k,o,j}$ can only represent an upper bound estimate of the days invested in informal learning in the year. The lower bound number of days instead ($\underline{d}_{k,o,j}$) is estimated as corresponding to the number of days associated to the “Peer Learning” only, or:

$$\underline{d}_{k,o,j} = d^p \quad (4b)$$

In this latter case, double counting is avoided by including only one activity, even when the employee reports to be engaged in more than one type of informal learning.

Finally, the frequencies reported by PIAAC individuals about their “Peer Learning”, “Learning-by-Doing” and “Knowledge Updating” activities refer to the number of days in the year when these activities take place. Such training, however, most likely does not last for the entire day, and estimating investment

25. Furthermore, there is no hint that the questionnaire was submitted considering the three activities as independent one from the other.

in informal learning requires knowing the number of hours per day that are spent in informal learning, on average, by each employee.²⁶

To the authors' knowledge, only three papers report such estimates: Loewenstein and Spletzer (2000) for the U.S. in 1993-1994, Kurosawa (2001) for Japan in 1994, and Nelen and de Grip (2009) for the Netherlands in 2007. Annex 2 reports how the different estimates were made comparable, and shows that different types of employees engage in significantly different spells of informal learning depending on the country they belong to and the year in which informal learning takes place. In particular, the figure for the Netherlands is substantially higher than the corresponding one for the U.S. or Japan, even after discounting for differences in the time of the survey and the definition adopted for the survey.

For the purpose of this study, a conservative approach is again followed, whereby an average of the hours of training per day for Japan and the U.S. is used and applied to all other countries. More precisely, an average of the figures for supervisors and co-workers is taken for the U.S., and then averaged once again with figures from Japan. This procedure yields a value of 0.57 hours per day of informal learning (i.e. about half an hour) for employees with job tenure lower than one year, and 0.24 hours (about a quarter of an hour) for employees with longer job tenure. These values are summarised in a vector $z_{k,o,j} = \{0.57; 0.24\}$, where the applicable value depends on the employee k 's tenure. These figures have the appealing property of decreasing with tenure, which is coherent with the intuition that newly hired employees require more (informal) training when joining a company. Data on individuals' tenure on the job is available from PIAAC.

Summarising the steps mentioned thus far, the upper and lower bound investment in informal learning is estimated, respectively, as:

$$\begin{aligned}\bar{I}^{IN} &= \sum_{k,o,j} (\bar{d}_{k,o,j} z_{k,o,j} w_{k,o,j}) \\ \underline{I}^{IN} &= \sum_{k,o,j} (\underline{d}_{k,o,j} z_{k,o,j} w_{k,o,j})\end{aligned}\quad (5)$$

The three papers mentioned above also report an estimate of the number of hours of informal learning in a year. It would be possible, as a consequence, to derive the measure of interest without PIAAC. This, however, would be less than optimal, as using PIAAC data as well should reduce the impact on our estimates of possible country specificities in reporting the data. What is more, the information for the U.S. and Japan was collected in 1993 and 1994, i.e. more than twenty years ago, and this time distance may lead to severely underestimating or overestimating investment in training if used alone. Combining these data with the more recent information contained in PIAAC therefore aims at limiting such possible biases.

As a consequence, according to equation 1 to 5, the total (lower bound) investment in training can be estimated as:

$$\begin{aligned}I &= \sum_{k,o,j} w_{k,o,j} (p_{k,o,j} h_{k,o,j} + p_{k,o,j} h_{k,o,j}^N + \underline{d}_{k,o,j} z_{k,o,j}) + \\ &+ \sum_{k,e,o,j} (q_{k,e,o,j}) \frac{C_e}{S_e} + \sum_{k,o,j} (q_{k,o,j} h_{k,o,j}^N C_j^N)\end{aligned}\quad (6)$$

26. Similarly, only using the estimated number of hours per day and multiply them by the number of working days in a year would be inappropriate, as it should not be assumed that training takes place every day.

where the first term on the right side of equation (6) corresponds to the opportunity costs of an employee attending formal training, on-the-job training and informal learning and the peers or of supervisors involved in informal learning with her. The second and third terms estimate the direct cost of formal and of on-the-job training, respectively.

The formula in (6) therefore provides an estimate of the nominal investment in training at the occupation, industry or country level. In order for these figures to be comparable across industries and countries, they should be net out of macroeconomic considerations which may differently affect countries and industries. This can be achieved adjusting investment figures by purchasing power parity. Both cost and wage measures mentioned so far and used to estimate I are collected in local currency, at current 2010 prices. With the appropriate choice of PPP ratios, these can be made comparable (in PPP U.S. dollars), thus obtaining I^* , i.e. PPP-corrected estimates of investment in training.²⁷

As a last caveat, it should be noted that the methodology detailed thus far yields estimates of investment in firm-based training, while creating a time series of investment and capitalising such investment as to proved capital figures goes beyond the scope of this paper. As only one wave of the PIAAC survey data has been collected at the moment of writing, it is impossible to test the sensitivity of the methodology to the use of data related to other time spans, and to verify their coherence with the other structural figures and consistency over time. The best that can be done at present to estimate investment in training for different years would be to exploit time series of wages and incidence of training from external sources and assume p and q to be constant over time²⁸. The Perpetual Inventory Method (PIM), a standard way to capitalise investment, also in the KBC measurement literature, could then be applied to this time series of investment. Pursuing this endeavour, however, would require making further assumptions about, among others, (i) the most appropriate price for training, and (ii) the service life, decay and depreciation of training as a KBC investment. As said, all this goes well beyond the purpose of the current paper.

Public vs private sector investment in training

The methodology proposed thus far aims to estimate investment in training independently on the institutional nature of the firm or establishment where workers are employed, i.e. a privately-owned company, or a non-market institution, be it a public entity (i.e. either a part of the public administration or a government-sponsored firm), or a not-for-profit institution.

While existing estimates, mostly relying on the Corrado et al.'s (2009) analytical framework, usually encompass the business (or market) sector only, a more complete assessment of KBCs as sources of productivity and economic growth would however benefit from the measurement of intangible investment

27. The current study uses the 2010 PPP values for GDP computed by the OECD. It may be argued that a measure of prices for GDP does not correct price differences in training appropriately, as the proposed estimate of expenditure in training relates more closely to wages than to GDP at large (O'Mahony, 2012). Criticism to the use of GDP deflators for specific kinds of KB assets whose price is not reported in national accounts is proposed by Corrado et al. (2011), too. However, their criticism refers to the time dynamics of prices within a given country, while this study only requires different international prices in a precise year. What is more, their criticism applies to investment in R&D, whose price declined in recent years in most OECD countries, contrary to the general level of prices as captured by GDP deflators. The same should not apply when considering investment in training, as wages typically increase with time, often at a faster rate than GDP.

28. This approach, too, can be criticised, since (i) it assumes that p and q do not vary with the business cycle, which is questionable in light of the literature review on the cyclicity of training which was proposed above; and (ii) it aggregates individual-level p and q at the industry or country level, which discards part of the useful information embodied in the microdata.

in the non-market part of the economy. A first attempt to provide an SNA-compatible estimation methodology for all classes of KBC assets is proposed in Corrado et al. (2015). The authors provide estimates of non-market investment in KBC for the following industries: scientific research and development (ISIC Rev.4 sector 72); public administration and defence (84); education (85); health and social work (86-88); and arts, entertainment and recreation (90-93).

The present analysis estimates public investment in a different way. It exploits the availability of information about the private, public or non-profit nature of the institution in which surveyed individuals work, as reported in PIAAC.²⁹ As a consequence, estimates of I for each of these sub-sections of the economy can be obtained using Equation 6 and restricting the population of interest according to the institutional nature of the workplace. Compared to Corrado et al. (2015), PIAAC micro-level data grant the possibility to account for the private or public nature of firms in all industries, including e.g. public firms in industries which would not usually be classified as public-services, like transportation and electricity production (two investment-intensive ones). Nevertheless, to enhance comparability with ongoing studies, public sector estimates in the present paper relate to the five non-market industries reported in Corrado et al. (2015) and here above. Within these sectors, the availability of microdata permits to exclude private firms in sectors usually classified as non-market, like education, hence to avoid assumptions on the relative size of public vs private investment within a given sector. This appears especially important since both non-market and market entities are operating in four out of the five industries mentioned above (Corrado et al., 2015).³⁰

The implemented definition of public ownership in PIAAC, however, does not distinguish between public owned firms and other public institutions which may invest in KBC (in Corrado et al., 2015, these are defined, respectively, “government-sponsored enterprises” and “general government”). If this allows a more encompassing assessment of the role of public investment in the economy, it also reduces comparability with the already scant literature and the SNA, which excludes publicly-owned firms from the boundaries of the non-market economy.

A final concern on the application of Equation 6 to public investment may arise if one assumes the relationship between workers’ salaries and productivity to be different in private firms relative to public and non-profit entities. Neglecting such differences may bias both the direct and the opportunity cost of training, which are a function of the individual’s wage. It should be stressed, however, that the link between wages and productivity in the proposed methodology is mediated by the discount factors p and q , so that only a fraction of the expenditure on wages is considered as investment. As p and q are worker-specific, they also change depending on the institutional nature of the workplace, if it is the case that the latter impacts the usefulness and location of the training spell, or the proportion of training cost paid by the employer.

Investment in formal and on-the-job training and in informal learning: first descriptive evidence

Incidence of training

In what follows, some descriptive statistics on the number of interviewed individuals who received training, by type of training and skill of the individual, are displayed. Skills are categorised in three classes

29. Question D_Q03 (ref. Annex 1).

30. This relies on the accuracy of the answers to question D_Q03 in PIAAC. The questionnaire correctly specifies, for instance, that “private companies in which the government is minority shareholder should be classified as belonging to the private sector”. If the government is (at least) majority shareholder, as a consequence, firms are classified as publicly owned.

(“High”, “Medium”, “Low”) based on occupational information reported by the individual in PIAAC. This classification is based on the ILO mapping of ISCO classes into skill levels (ILO, 2012).^{31,32} The focus is on the incidence of training, i.e. the number of employees who are involved in training, rather than on its intensity, i.e. on the number of hours spent in training by the employees - the intensity of training will be conveyed in terms of monetary investment further below.

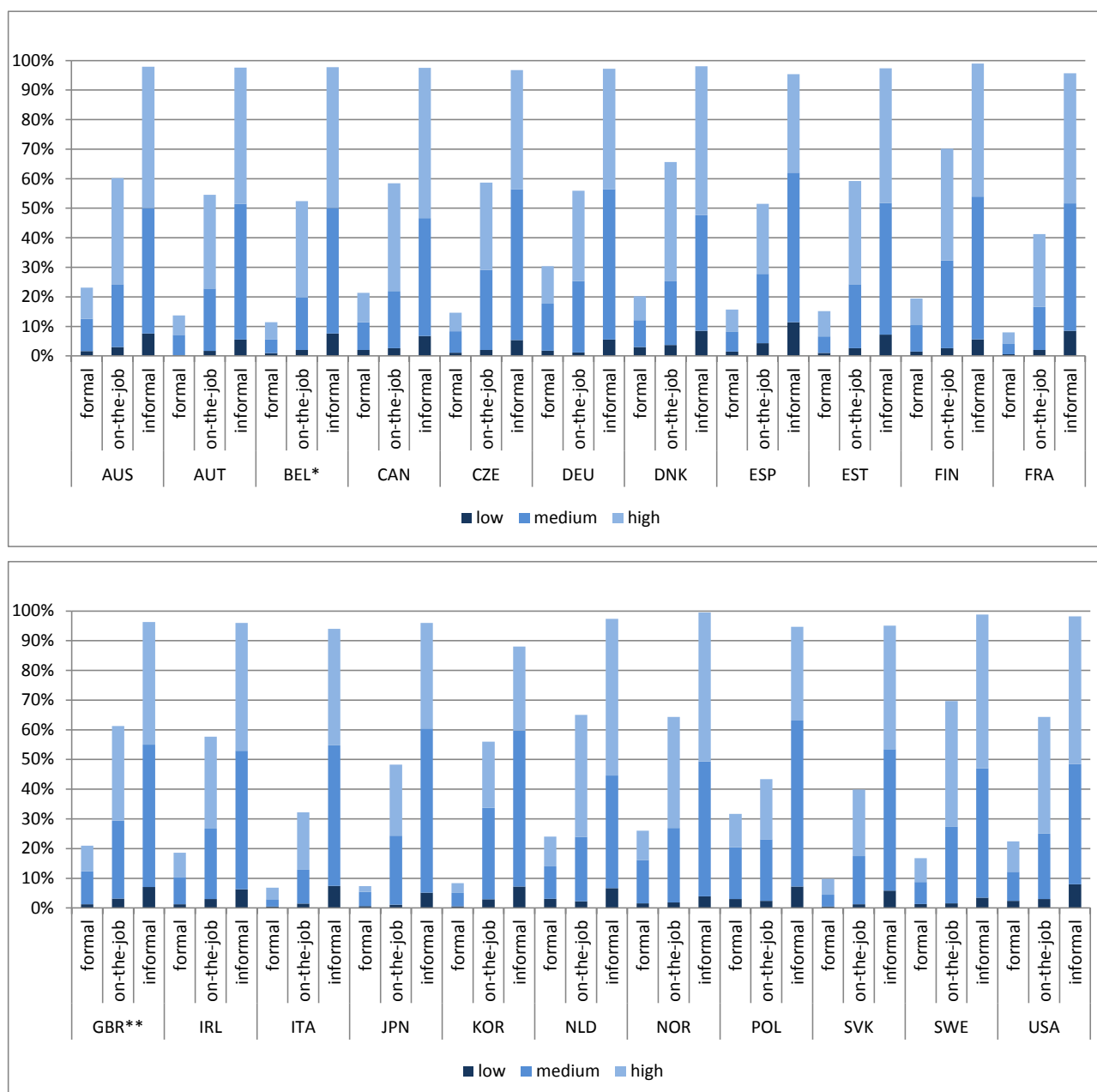
Almost all surveyed individuals who are either employed or self-employed received some training in the sample years, in all countries considered. The number of highly skilled and medium skilled individuals receiving some training represents approximately the same proportion of total employees (40 to 50% for each category of skill) across all countries considered. Also, training of low skill workers accounts for less than 10% of total employment in each country.

Figure 1 provides more information in this respect, by breaking down incidence by type of training. Percentages are calculated as the country-specific number of individuals in each skill category receiving a specific type of training, over the total number of employees and self-employed individuals interviewed in PIAAC. The figure shows that in all countries, 97% of individuals in employment were exposed to some informal learning on average between 2011 and 2012. On the contrary, on average only 18% of individuals in employment stated to have benefited from formal training, with the notable exception of Italy, Japan, France, Korea, the Slovak Republic and Belgium, where these figures are approximately halved. However this does not necessarily lead to lower-than-average incidences for Belgium, Korea and Japan when on-the-job and formal training are considered together.

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31. ILO (2012), page 14: “High Skill” corresponds to ISCO-08 one digit occupations 1 to 3 (managers, professionals, technicians and associate professionals), “Medium Skill” to ISCO-08 occupations 4 to 8 (workers in clerical support, services and sales, skilled agriculture and forestry, crafts and related trades, plants and machine operators), and “Low Skill” to ISCO-08 occupation 9 (elementary occupations). Armed forces workers are excluded from the present analysis altogether.
32. As the current methodology rather exploits the ILO classification, “low-skilled workers” should be understood as “workers employed on low-skilled occupations”. An alternative classification of workers could rely on the individual’s actual literacy, numeracy and problem-solving skills as recorded through PIAAC tests. As individuals may not be employed in an occupational category which fits their real skills (mismatch), this approach would perhaps more accurately assign skill levels to individuals. This is left to future work. .

Figure 1: Incidence of training by type of training and skill level, as a percentage of total employment, by country.

Selected countries (Average of 2011 and 2012)



Source: Authors' calculations on the PIAAC sample. Percentages reflect the number of individuals in each skill category receiving the specific type of training, over the total number of employees in the same country in PIAAC.

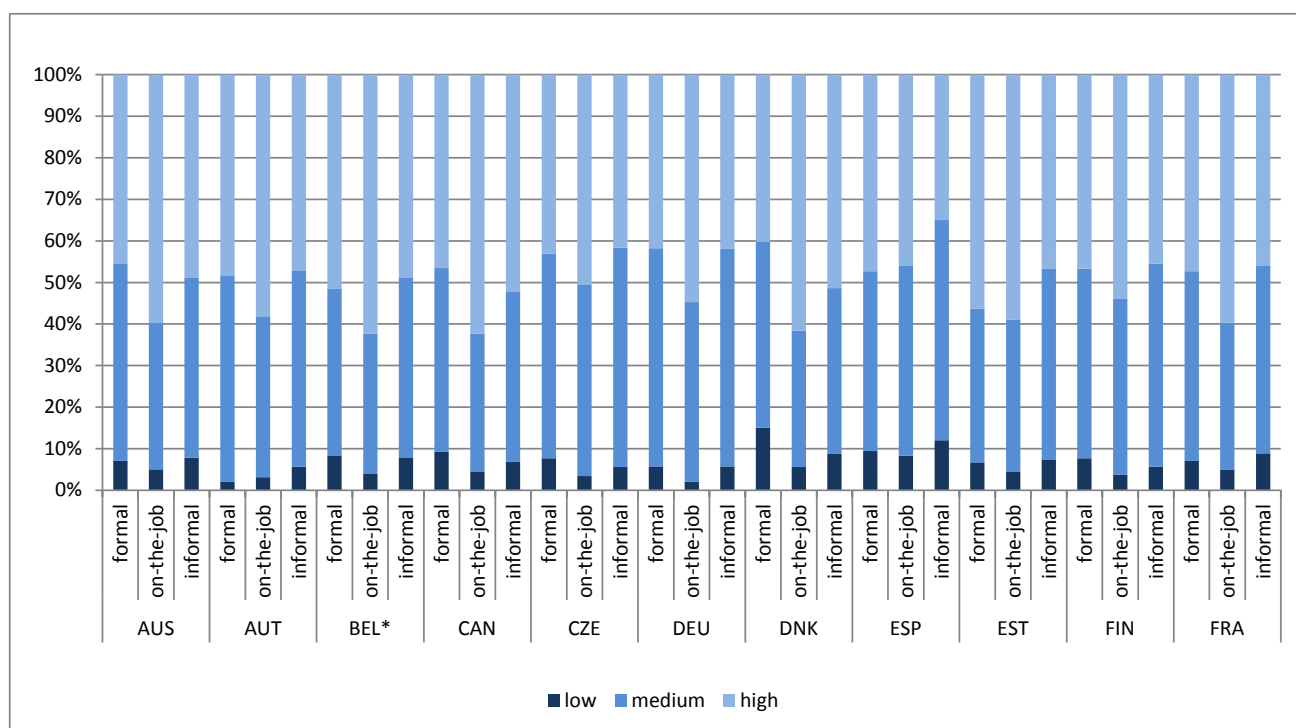
* PIAAC data from Belgium only cover Flanders. ** PIAAC data from the UK only cover England and Northern Ireland.

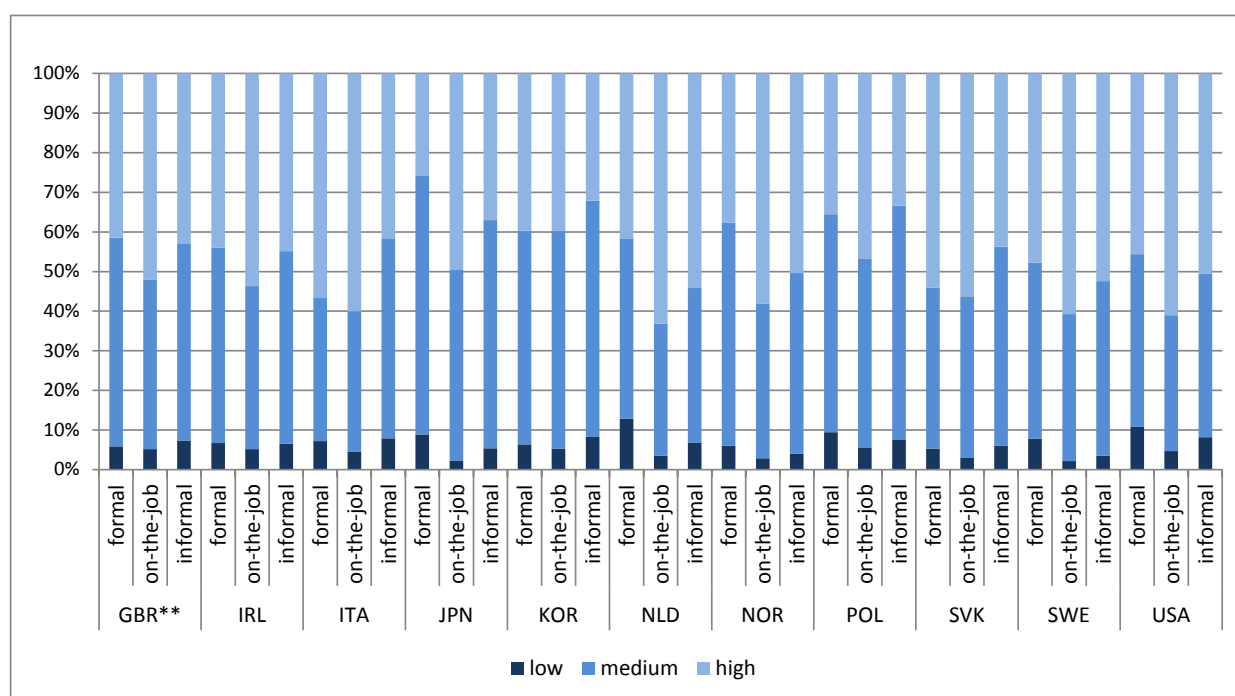
Within each type of training, low-skilled workers typically account for the lowest proportion of total employment, with higher percentages for informal learning than for other types of training. This information is better captured by Figure 2. It reports the incidence of training as a percentage of trained people in the PIAAC sample, by skill and type of training. Among all workers receiving training, low skilled employees are the least represented, independent of the type of training and the surveyed country. More precisely, less than 10% of employees receiving each type of training display low skills, with

consistently lower percentages when the training is on-the-job (about 4% of the employees receiving on-the-job training is low skilled). Low and medium skilled employees represent a lower percentage of total employment (approximately 44%) in on-the-job training than in other forms of training (approximately 55%).

Skills and firm level training therefore seem to be positively correlated and especially so for on-the-job training, coherent with training being an instrument through which employers can gain the loyalty of employees and limit turnover of key workforce. This positive correlation holds especially when skills are expressed as a function of education, since more educated individuals should be able to extract a higher return from training than less educated individuals, as highlighted in previous studies (Brunello, 2003, Bassanini et al., 2007).

Figure 2: Trained individuals by type of training and skill level, as a % of individuals receiving the same type of training.
Selected countries (Average of 2011 and 2012)





Source: authors' calculations based on the PIAAC sample. Each percentage is calculated as the number of individuals in each skill category receiving the specific type of training, over the total number of employees receiving the same type of training in the country in PIAAC. * PIAAC data from Belgium only cover Flanders. ** PIAAC data from the UK only cover England and Northern Ireland.

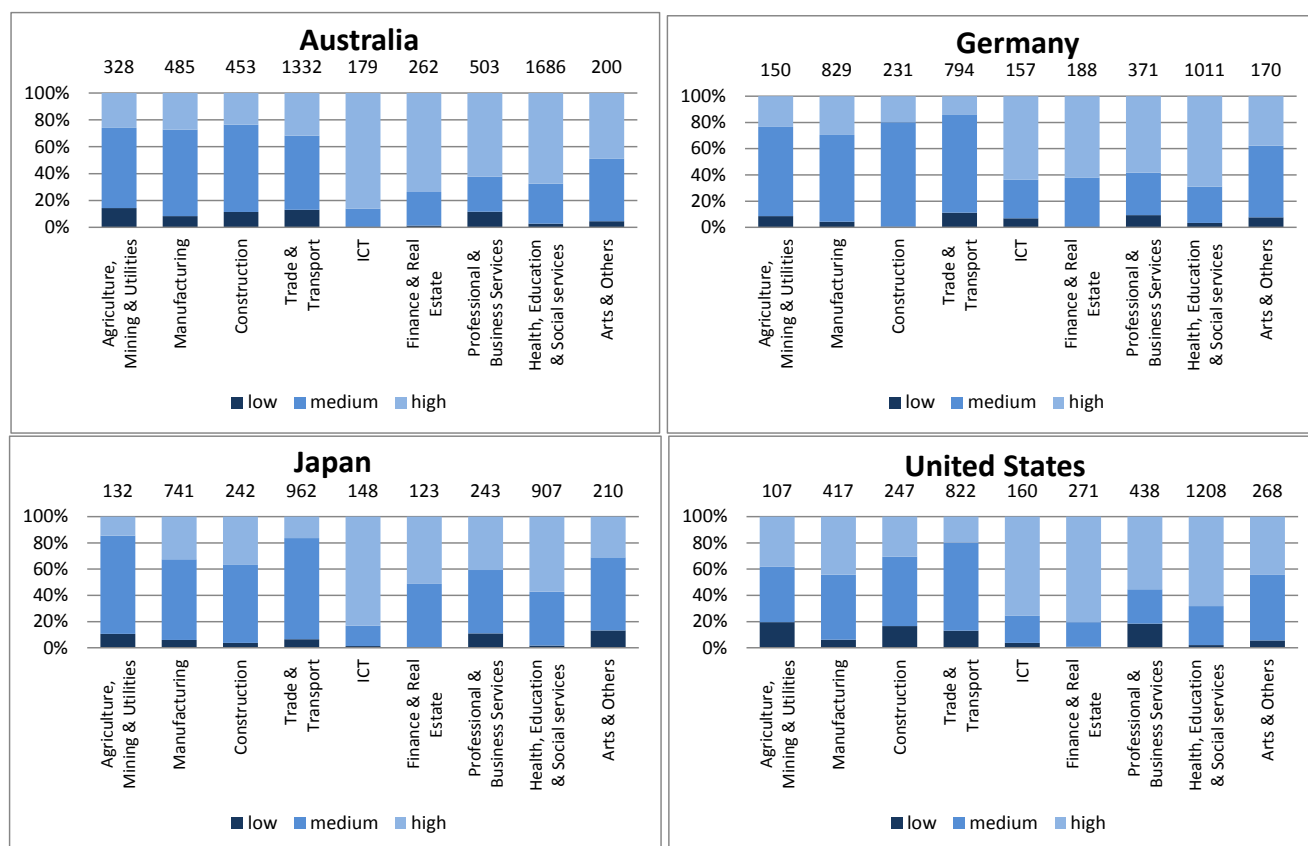
Figure 3 displays the incidence of training by skill level and one digit ISIC4 sector as a percentage of employees receiving at least some training. In the interest of space, the figures reported relate to four countries only, one per each continent.³³ The number of interviewed individuals who received some training and operated in the industry of interest³⁴ is reported above each bar.

33. In addition, Germany can be considered as an example of manufacturing-intensive countries, and Australia for resource-intensive countries. Reporting the U.S. allows a comparison to the investment patterns first offered in Corrado et al. (2009).

34. The industry labels in the graphs are here declined with more precision. "Agriculture" refers to ISIC4 sector A, "Mining and Utilities" to sectors B, D and E, "Manufacturing" to sector C, "Construction" to sector F, "Trade and Transportation" to sectors G (trade), H (transportation), and I (accommodation and food services), "ICT" to sector J, "Finance" to sector K, "Real Estate" to sector L, "Professional and Technical" to sectors M (professional services) and N (administrative services), "Health, Education, Social Services" to sectors O (public administration), P (education) and Q (health services), "Arts and Others" to sectors R, S and T (respectively, arts, other services and household employers).

Figure 3: Incidence of training by skill and industry as a % of trained employees.

Selected countries (Average of 2011 and 2012).



Source: authors' calculations. Above the bars is the absolute number of interviewed individuals operating in that sector receiving at least one type of training.

Finance, real estate, ICT and health, education and social services display especially low percentages of trained employees who are low-skilled. Trained employees in services in general seem to be more often high skilled than individuals in other sectors, with the exception of the retail, transportation, and food and accommodation sectors. The latter sector and agriculture (with the exception of the U.S.) display the lowest percentage of high skilled employees who receive any training.

On the one hand these descriptive statistics may simply capture the different skill composition of industries. If an industry is especially intensive in low-skill workers, it may be the case that one witnesses more frequent training for the low-skilled than for other categories. On the other hand, considering that returns to training may be higher for skilled employees, the percentage of trained employees by skill may not simply reflect the skill composition of an industry. Figure 4 therefore reports the percentage of employees of a given skill type and sector who receive training.³⁵

35. "Production" includes sectors B to E. "Business services" include sectors G to N. "Public services" include industries O to Q. Adding R, S and T to "Public services" would not substantially change the interpretation of Figure 4.

Figure 4: Percentage of employees receiving training, by skill level and type of training

Selected countries (Average of 2011 and 2012)



Source: authors' estimations based on PIAAC. The sectoral breakdown is explained in footnote 30.

The percentages for informal learning have been omitted, as almost everyone in the survey reports to have received some informal learning during the sample period. The percentage of high skill workers who receive on-the-job training is always larger than the percentage of, respectively, medium and low skill workers in the same situation, independent of the sector or country considered, except for the business sector in Australia. The same pattern is not found for formal training, where countries and sectors within a country display an important heterogeneity, with the exception of business services, where formal training is decreasing in the level of skill. Another clear pattern that emerges relates to the percentage of workers receiving on-the-job training: this is usually higher than the percentage of workers who receive formal training, across skills, industries and countries. An exception to this pattern can be found in Germany for the low-skilled in services and in the economy as a whole, where the percentage of low-skilled workers receiving formal training is higher than the percentage of low-skilled workers receiving on-the-job training.

Investment in training

The methodology in this study allows estimating investment in training at the industry and country level for the year of reference. Figure 5 reports the estimates of total investment in formal training, on-the-

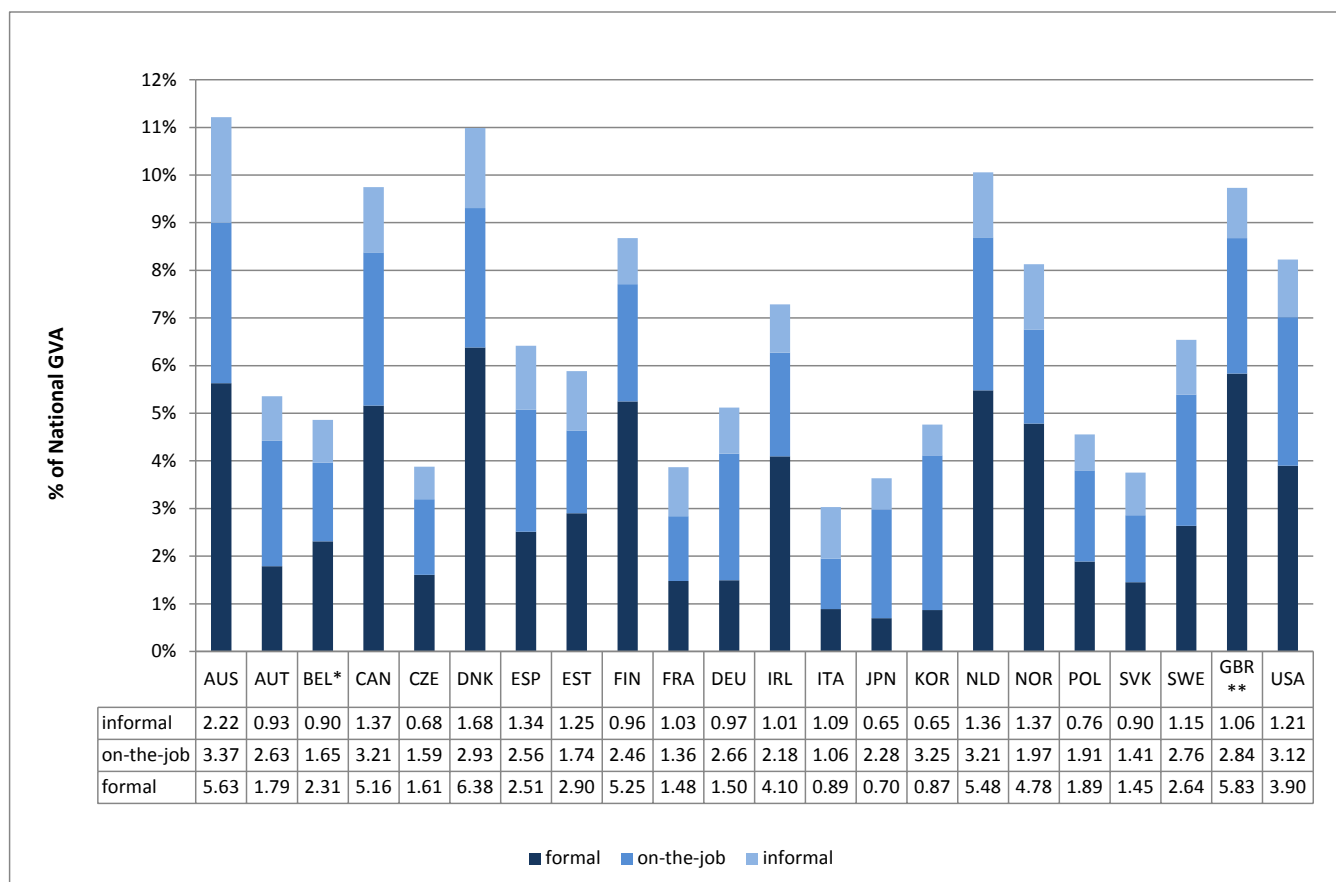
job training and informal learning as a percentage of countries' GDP, where the total figures have been computed taking into account the lower bound estimates for informal learning.³⁶

Notable differences in countries' investment in total training emerge, with Australia, Denmark, the Netherlands, Canada and the UK exhibiting substantially more training - as a percentage of Gross Value Added - than the other countries in the sample. The same can be said when looking at on-the-job training, although country differences in this case are much less pronounced.³⁷ The magnitude of the on-the-job training estimates is, understandably, much lower, reaching between 30 to 50% of total investment. In particular, median formal training accounted for 2.58% of GVA vs 2.51 for on-the-job one and 1% for informal one. Informal learning accounts for a lower percentage of GVA (1.1 percent on average across countries), despite the fact that almost all workers report to have undergone some. Cross country differences may be explained by national specificities in the number of hours of training (vs number of employees involved) and real wage dynamics.

Although cross-country heterogeneity in intensities seem to be mainly driven by formal training, many other factors may contribute to explain the stylised facts reported above, including differences in framework conditions, in the propensity of firms to invest in human capital, or in the turnover of employees and the consequent need or not to (re)train the employees. While explaining country-specific patterns is left to future research, it may still be important to highlight how the low incidence of total training for Korea and Japan may reflect low levels of employment turnover. This is especially true for Japan, where not only total training but also on-the-job training intensity is relatively low in comparison to other countries. On-the-job training constitutes 38% of total investment in training on average in all countries, with the notable exception of Germany, Japan and Korea, where it represents more than 50% of total training and becomes the most important component.

36. These estimates are calculated taking into account the appropriate sampling weights, contrary to the figures shown before, which only described the sample interviewed in PIAAC, estimates here rely on the appropriate sampling weights. At the denominator average Gross Value Added (GVA) in current prices between 2011 and 2012 is used, since individuals in PIAAC were asked to report information about their training status "in the previous 12 months" with respect to the moment of the interview, which refers a time period between 2011 and 2012.

37. Dispersion of country-level intensities in formal training is double (approximately 60 vs 30 percent) than that of on-the-job training and informal learning.

Figure 5: Investment in training as a percentage of GVA


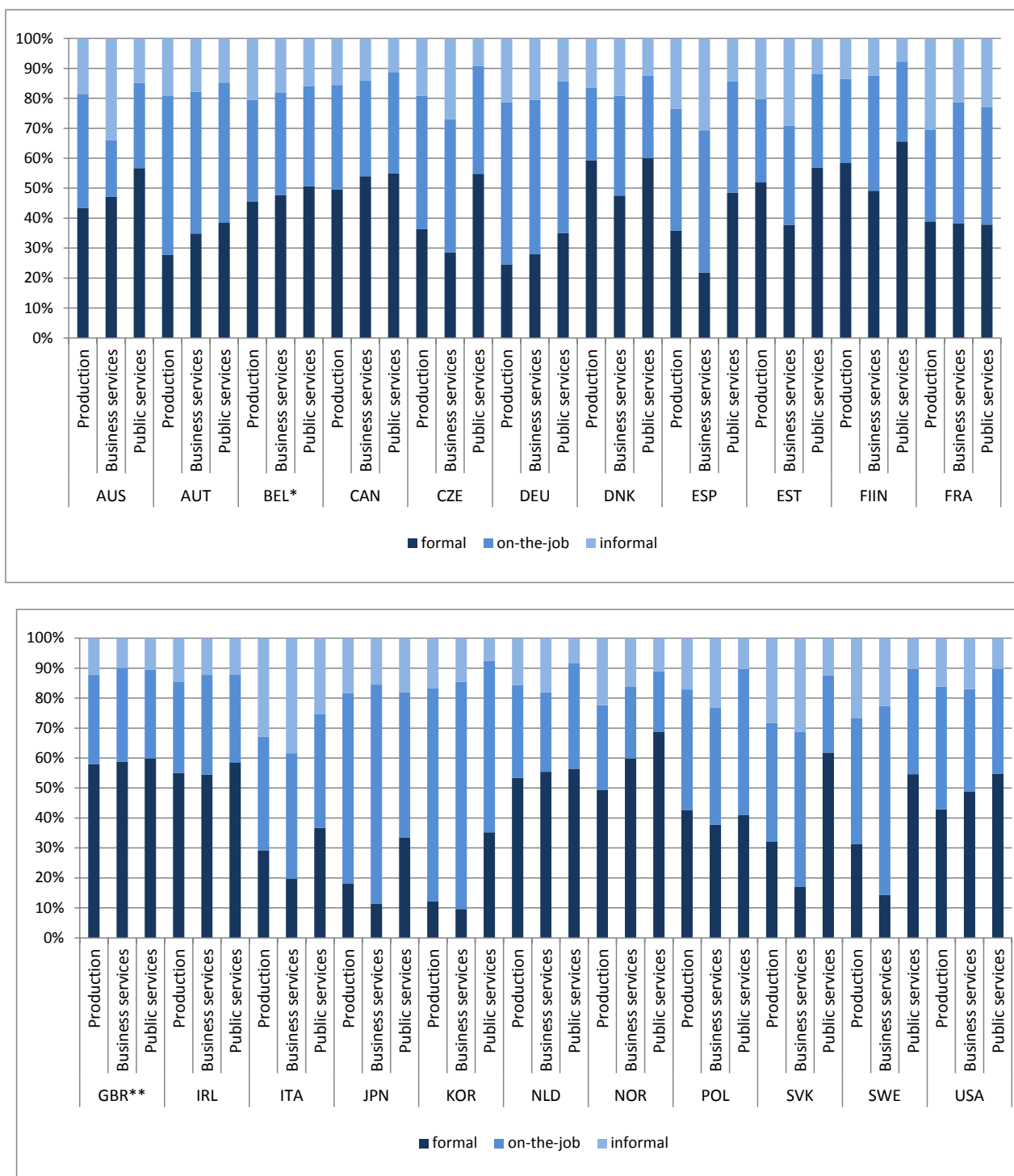
Source: authors' own calculations based on PIAAC.

* PIAAC data from Belgium only cover Flanders. **PIAAC data from the UK only cover England and Northern Ireland.

Figure 6 reports the breakdown of total investment by type of training and macro-sector, i.e. production, business services and public services. The specific industry that PIAAC respondents belong to does not seem to matter for the relative importance of investment in on-the-job training. In other words, when on-the-job training is important with respect to other forms of training, this usually is the case in all three macro industries. Notable exceptions are the Czech Republic, the Slovak Republic, Japan, Korea, Sweden and Spain. Investment in on-the-job training is on average more relevant in business services than in production (with the exception of Australia), while public services seem to be more intensive in investment in formal training than other sectors. Public services further appear to be more intensive in formal training than the aggregate economy throughout the sample.

France, Germany, Italy, Japan, Korea and the Czech Republic, arguably all manufacturing-oriented economies, are characterised by a lower weight of formal training in total training investment, irrespective of the macro-industry of interest, and contrary to the other economies in the sample. This might also be due to the different way in which formal training is provided in the countries considered. Australia, Canada, the United Kingdom and the United States are countries where tuition fees are comparatively higher than those of the other countries in the sample, and where formal education is often provided by private institutions. This may inflate the estimated investment in formal training, as the cost per student might be comparatively higher in countries where private education is more common and tuition fees are generally higher. Countries usually invest relatively less in informal learning than in other forms of training, with the exception of Italy and the Slovak Republic, especially in production and business services industries.

Figure 6: Investment in training by type and industry, as a % of total training investment in the industry



Source: authors' estimations based on PIAAC. The sectoral breakdown is explained in footnote 30. * PIAAC data from Belgium only cover Flanders. **PIAAC data from the UK only cover England and Northern Ireland.

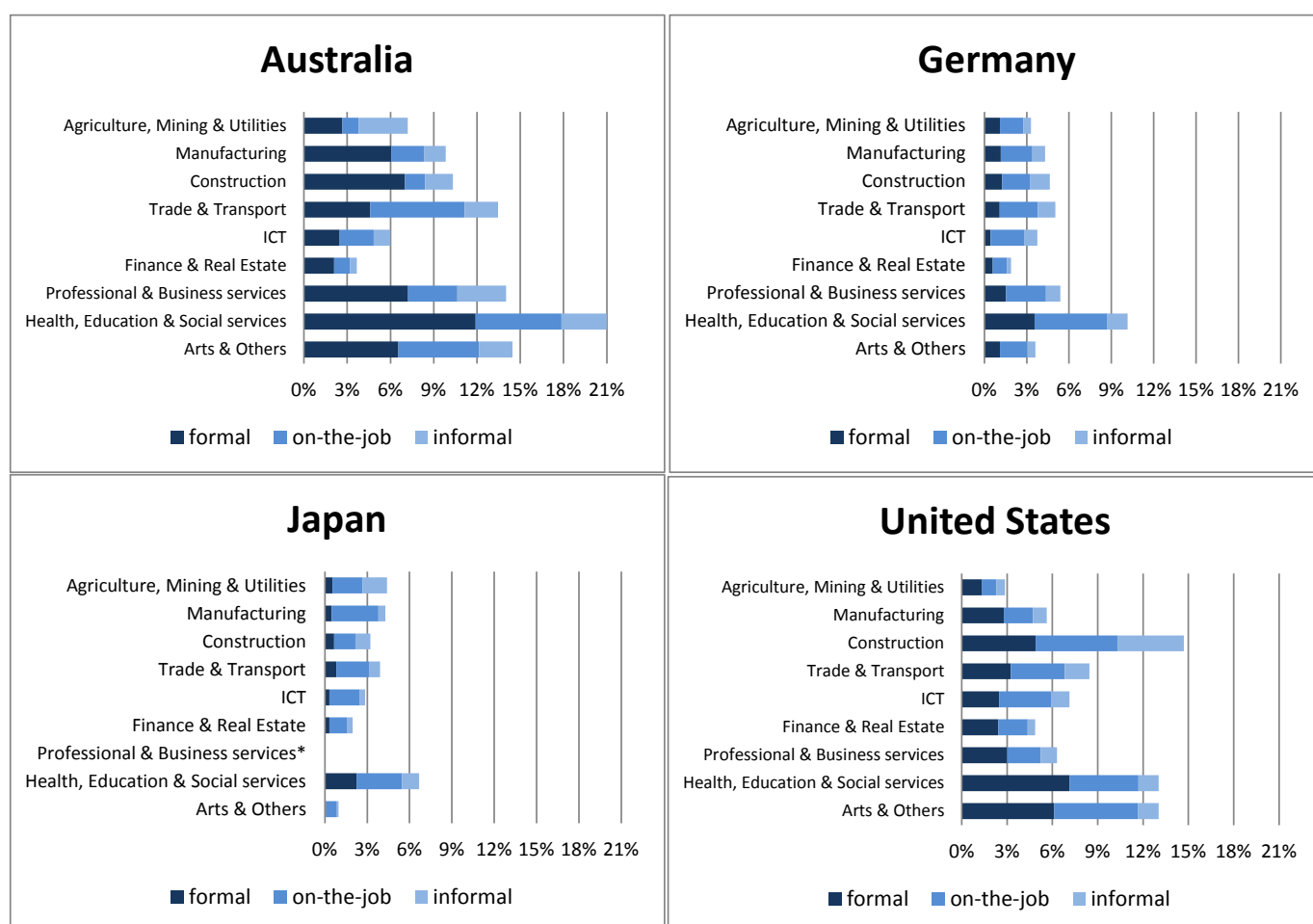
To investigate the extent to which countries' differences in the magnitudes of the investment in training can be – at least partially - explained by differences in the production structure of the country, and in the relative intensity in training of industries, industry-specific estimates are proposed. Figure 7 shows a

more refined industry breakdown of investment in training as a percentage of industry GVA for Australia, Germany, Japan and the United States.

The relative intensity of Australia in formal training and of Japan and Germany in on-the-job training is reflected at the industry level as well, while the picture is mixed for the United States. Training investment intensity in the U.S. manufacturing sector is lower than expected, if one considers technology intensity in that sector, and the consequent need to adapt to change of its workforce, but it still reaches 6% of the industry GVA. On-the-job training is important (as a proportion of GVA) in the information and telecommunication sector, in professional and business services, manufacturing, and especially in public services. The United States further displays a relatively higher intensity of on-the-job training than Germany, across all industries, except public services. Some national specificities call for further investigation, such as the high investment intensity in the trade and transportation sector for Australia and the construction sector in the United States. This is left to future research.

Figure 7: Investment in training by type and industry, as a % of GVA in the industry.

Selected countries (Average of 2011 and 2012)



Source: authors' calculations based on PIAAC. * Wages information for the sectors M&N is unavailable for Japan for the years considered.

Public investment

Thanks to the availability of information in PIAAC about the institutional nature of the individual's workplace (private company, public entity or non-profit organisation), it is possible to separately estimate the contribution of the public sector on KBC investment. In what follows, public investment relates to public companies operating in one of the five macro sectors identified in Corrado et al. (2015) as especially intensive in public investment (ISIC Rev.4 industries 72 and 84-93).³⁸

First summary statistics suggest that 20 percent of the total reweighted sample is composed by individuals working in public entities, either publicly-owned companies or public institutions.³⁹ This percentage rises up to 53 percent when focusing only on the industries where public ownership is more frequent, as in Corrado et al., 2015. Among these industries, public administration and education display the highest proportion of public employment over total employment on average across country (respectively, 94 and 78 percent), while other community and personal services display the lowest (21 percent).

Table 6: Incidence and investment in training in public entities, by type of training.

Selected sectors (Average of 2011 and 2012)

Country	Employment (% of public sector employment)			Investment (% of corrected public sector GVA)		
	Total	Formal	On-the-job	Total	Formal	On-the-job
AUS	99.5%	23.8%	84.1%	20.7%	11.5%	6.3%
AUT	98.3%	13.3%	70.9%	8.4%	3.5%	3.7%
BEL*	98.8%	12.1%	64.9%	7.3%	3.5%	2.6%
CAN	99.3%	19.6%	79.2%	17.1%	9.2%	6.0%
CZE	97.9%	17.3%	73.5%	8.9%	5.3%	2.9%
DEU	98.2%	14.7%	72.8%	8.3%	3.0%	4.1%
DNK	99.3%	19.4%	79.9%	17.7%	10.5%	5.0%
ESP	99.1%	20.4%	73.9%	13.2%	5.4%	5.6%
EST	99.4%	19.2%	81.4%	10.7%	6.3%	3.3%
FIN	100.0%	21.7%	84.6%	14.8%	9.5%	4.2%
FRA	98.8%	8.7%	56.3%	7.3%	2.6%	3.0%
GBR**	98.9%	21.8%	79.2%	16.9%	10.2%	4.9%
IRL	97.8%	17.6%	74.0%	15.1%	8.5%	4.6%
ITA	97.7%	9.6%	47.9%	5.0%	1.7%	1.9%
JPN	99.5%	7.8%	66.4%	4.7%	1.4%	2.5%
KOR	98.5%	12.1%	85.5%	8.0%	2.2%	5.2%
NLD	99.6%	22.3%	81.9%	18.3%	10.5%	6.4%
NOR	99.6%	26.3%	73.7%	16.6%	11.4%	3.5%
POL	98.0%	29.4%	66.2%	9.9%	3.9%	4.8%
SVK	95.5%	15.6%	51.6%	8.3%	5.0%	2.2%
SWE	99.7%	20.0%	80.5%	14.2%	7.6%	5.1%
USA	99.8%	23.5%	82.3%	8.2%	4.4%	3.1%

38. The definitions of public employment and investment are not identifying the same sub-section of the economy as "Public services" in Figures 4 and 6, as it also includes sector 72 and it excludes all private and non-profit organisations operating in the same sectors.

39. An additional 4 percent work in non-profit organisations.

Source: authors' own calculations based on PIAAC. The frequencies are calculated as the number of employees in public entities who received training at least once in the period, over total employment in public entities in ISIC Rev.4 sectors 72 and 84-93. Investment is deflated by gross value added which was corrected as explained in the text. "Total" includes all types of training.

* PIAAC data from Belgium only cover Flanders. ** PIAAC data from the UK only cover England and Northern Ireland.

The first three columns of Table 6 report instead the proportion of employees working in public entities and receiving training, as a percentage of the total employment in all public entities in the considered sectors. The values for formal training and total training are almost the same as in the total economy (17 and 99 percent, on average across country), while the figures substantially differ for on-the-job training. 73 percent of public employees in these sectors receive on-the-job training, vs approximately 50 percent of employment in the total economy.

The public sector also invests more in training than the private sector and the overall economy: on average, across countries the ratio of investment over GVA in the overall economy reaches only 60 percent of the same ratio for the public sectors considered.⁴⁰ Investment intensity for total training is still lowest in Italy, Japan and France, but still significantly higher than in the total economy. This result is driven by formal training, which is predominant in the public sector (twice as much as in the overall economy, on average). This to some extent may reflect the presence of the education sector itself in the public sector, where the likelihood of investment in formal training is higher. The dispersion in investment intensity in formal training is also almost double for the public sector than in the overall economy (as measured by the coefficient of variation among countries' intensities), possibly reflecting the high cross-country heterogeneity of the education sector.

Robustness checks

This section aims to assess the robustness of the proposed training estimates by: (i) comparing the obtained estimates with the key references in the literature: (ii) shedding light on the possible consequences of some of the key methodological choices made, namely the way in which p and q are computed: and lastly (iii) by making use of another variable reported in PIAAC to double check the accuracy of the results obtained.

On-the-job training is the type of training closest to the concepts of continuous and on-the-job training which have been usually explored in previous studies. Such studies typically have no information on informal learning, and do not incorporate investment in the formal type as a common practice. The estimates of on-the-job training presented here above are therefore the only ones that can be compared with estimates of investment in training reported in the literature.

The studies by O'Mahony (2012) and Corrado et al. (2014) are taken as reference points, as they represent the most recent and methodologically closest investigations to our study. Table 7 reports the comparison across the estimated intensities for the total market sector and the production sectors across the three methodologies.⁴¹ The estimates obtained with the methodology presented in this study do not appear

40. Investment intensity is calculated as a proportion of gross value added, which has been decreased by a proportion equal to the percentage of public employees in the mentioned sectors of the economy. Using the entire value added of the sectors of interest would have been inappropriate to deflate public investment, as such figures of value added would be the product of both private businesses and non-market entities.

41. The market sector is composed by private companies only, independently on their industry of operation, hence estimates differ from those reported in Fig.5. . The denominators used to construct the shares are the following: GVA at current prices for the present study; value added calculated in a manner consistent with the estimation of investment in intangibles for Corrado et al. 2014; and a modified estimate of value added including investment in training for O'Mahony (2012); GVA at current prices for the present study,

to be biased univocally upwards or downwards with respect to the reference papers, neither for the total economy, nor for production (i.e. the sum of manufacturing, mining and utilities). Although higher estimates than the benchmark methodologies are obtained here for Germany, Spain and Sweden for total investment intensity, this is not the case for all other countries. What is more, the increase with respect to previous studies is of different magnitude for the total economy and the production sector. These differences may have been triggered by a number of factors, including the methodological choices made, the slightly broader definition of on-the-job training used by PIAAC as compared to existing studies; the reference period considered; and the sampling strategies used. However, all in all, the figures presented in this paper do not seem to alter the relative intensity of investment in training in those economies where a direct comparison with the two previous studies is possible.

Table 6. On-the-job training investment in the market sector as a percentage of GVA

	O'Mahony (2012)		Corrado et al. (2014)		On-the-job based on PIAAC	
	Total	Production	Total	Production	Total	Production
AUT	2.1%	1.3%	1.2%	1.0%	1.9%	2.0%
DEU	1.3%	0.9%	1.4%	1.5%	1.8%	2.1%
DNK	4.2%	3.1%	2.3%	1.6%	1.6%	1.9%
ESP	1.3%	0.9%	0.6%	0.5%	1.7%	1.8%
FIN	2.2%	1.2%	0.9%	0.8%	1.5%	2.0%
FRA	1.5%	1.5%	1.6%	1.3%	0.8%	1.8%
GBR**	4.4%	3.1%	1.6%	1.0%	1.8%	2.1%
IRL	0.6%	0.2%	1.8%	4.7%	1.4%	1.2%
ITA	0.3%	0.2%	0.9%	0.8%	0.8%	0.9%
NLD	2.5%	1.4%	1.4%	1.0%	2.0%	1.9%
SWE	1.5%	1.1%	1.1%	1.1%	1.7%	1.4%

Sources: O'Mahony (2012), Corrado et al. (2014) and PIAAC, where "on-the-job" stays for "continuous" training in O'Mahony (2012) and for "employer-based" training (vocational+apprenticeship) in Corrado et al. (2014). "Production" follows the definition of O'Mahony (2012) and refers to (NACE C-F) sectors. Data in O'Mahony (2012) are yearly averages over 2003-2007, in Corrado et al. (2014) they refer to the year 2010, in the present paper they refer to the average of 2011 and 2012. The market sector includes private entities only operating in any business industry. **PIAAC data from the UK only cover England and Northern Ireland.

As explained when describing the methodology, the computation of p and q entailed attributing a numerical value between 0 and 1 to each of the four possible answers to the "Subjective Usefulness" and "Allocation" questions. p and q for each individual were then computed averaging the individual-specific values obtained, duly highlighting (ref. footnote 12 and 14) the possible perceived arbitrariness of both choices. To investigate the sensitivity of the estimates to these choices, investment in training is recomputed changing one of the assumptions made at a time. In "Method 2", the "somewhat useful" and "mostly outside working hours" answers are given a value 0.25 instead of 0.33, while the "moderately useful" and "mostly during working hours" answers are attributed a value of 0.75 instead of 0.66. In "Method 3", answers are attributed values ranging from 1 to 4, with p and q that are obtained by multiplying the values attributed to the answers to each question, and then normalising the thus obtained results so that indicators are defined in a $[0, 1]$ interval.

without the correction presented in the previous paragraph, so as to enhance the comparison with other articles.).

Table 8 reports the estimates for total training obtained following each of the alternative methodologies proposed above. As can be seen, while the baseline methodology (the one used throughout the paper) and “Method 2” yield remarkably similar estimates, taking the product instead of the average of the answers to the “Subjective Usefulness” and “Allocation” questions lead to lower investment estimates across all countries considered. This was expected, as taking the product instead of the sum shifts the distribution of p and q towards the left and gives more weight to the individuals featuring lower values.

Table 7. Investment in total training as a percentage of GVA – Different methodologies

	<i>Baseline</i>	<i>Method 2</i>	<i>Method 3</i>		<i>Baseline</i>	<i>Method 2</i>	<i>Method 3</i>
AUS	11.22%	11.07%	9.26%	GBR**	9.73%	9.69%	8.15%
AUT	5.36%	5.37%	4.17%	IRL	7.29%	7.22%	5.66%
BEL*	4.86%	4.88%	4.12%	ITA	3.03%	2.92%	2.42%
CAN	9.75%	9.67%	7.62%	JPN	3.63%	3.60%	2.63%
CZE	3.88%	3.88%	2.96%	KOR	4.76%	4.78%	3.38%
DEU	5.12%	4.95%	4.16%	NLD	10.06%	10.04%	8.35%
DNK	10.99%	10.79%	9.45%	NOR	8.13%	8.17%	6.75%
ESP	6.41%	6.46%	4.71%	POL	4.56%	4.53%	3.20%
EST	5.89%	5.87%	4.54%	SVK	3.76%	3.77%	2.81%
FIN	8.67%	8.68%	6.53%	SWE	6.54%	6.54%	5.18%
FRA	3.87%	3.87%	3.44%	USA	8.23%	8.15%	5.94%

Source: authors' own calculations based on PIAAC. “Baseline” refers to the methodology used to issues the estimates reported so far; “Method 2” uses a different set of weights in the calculation of p and q for each surveyed individual; “Method 3” computes p and q as a product (instead of the average) of the responses to the underlying questions.

* PIAAC data from Belgium only cover Flanders. ** PIAAC data from the UK only cover England and Northern Ireland.

Table 9 further explores the robustness of the estimates to use of the different methodologies proposed by correlating the measures of investment in total, formal and on-the-job training at the 1-digit industry and country level.⁴² Table 9 highlights that the (Spearman) rank correlations of the different estimates are extremely high, both by training type and for total training. This is reassuring, as it implies that the different ways in which p and q can be specified do not drive estimates apart and do not change in essence the stylised facts depicted so far, despite the differences in magnitudes emerging from Table 8.

42. The estimates for informal learning do not change across methodologies, as they do not require p or q .

Table 8. Investment in training – correlations across different methodologies

		<i>Baseline</i>	<i>Method 2</i>	<i>Method 3</i>
Total	<i>Baseline</i>	1		
	<i>Method 2</i>	0.9856*	1	
	<i>Method 3</i>	0.9775*	0.9924*	1
Formal	<i>Baseline</i>	1		
	<i>Method 2</i>	0.9987*	1	
	<i>Method 3</i>	0.9875*	0.9890*	1
On-the-job	<i>Baseline</i>	1		
	<i>Method 2</i>	0.9995*	1	
	<i>Method 3</i>	0.9856*	0.9846*	1

Source: authors' own calculations based on PIAAC, Spearman correlations calculated on country/industry level data. * implies significance at the 1% confidence level. "Baseline" refers to the methodology used to issues the estimates reported so far; "Method 2" uses a different set of weights in the calculation of p and q for each surveyed individual; "Method 3" computes p and q as a product (instead of the average) of the responses to the underlying questions.

A further set of robustness checks relates to individuals' employment status in PIAAC. The estimates presented so far are based only on the responses of individuals who declare to be in employment, as this work is concerned with the measurement of investment in training at the industry level. Information on the status of each individual is contained in a derived variable constructed by the PIAAC team which is based on a number of questions contained in the survey. However, as PIAAC also asks the respondents themselves to state whether they are working or not, it is possible to double check the extent to which estimates based on the derived variable align with the estimates that would be obtained using respondents' original replies to the employment-status-related self-assessment question.

In particular, the employment-status-related question (c_q07) allows respondent to choose among ten categories, which can be synthesised as follows: Full-time employed; Part-time employed; Unemployed; Student; Apprentice or intern; Retiree; Disabled; Military; Domestic tasks. As can be seen from the reweighted frequencies of the "subjective status" by category and country reported in Annex 3, Table A9, on average 93% of the respondents identified as being in employment do report to be working at the time of the survey. This includes individuals in total and partial employment, those in the military or civil service, and apprentices. The remaining categories might have been included in the derived employment-status-related variable for a number of plausible reasons. Individuals reporting to be unemployed or retired may have been such at the moment of the interview, but may have told the interviewer to have been employed (for the majority of) the same year before participating to the survey.⁴³ A similar reasoning might apply to disabled individuals and, in any case, their disability condition does not entail the

43. It should be born in mind that PIAAC is a questionnaire that is administered by an interviewer, fact that raises the likelihood of obtaining additional relevant information.

impossibility of being in employment at the same time. Finally, individuals carrying out domestic tasks may have worked for some time in the year and be on temporary leave at the moment of the interview.⁴⁴

As can be seen from the discussion above, relying on the derived employment variable or on the self-reported employment status variable would lead to only marginally different results, and is a discussion therefore not worth pursuing any further. However, a self-reported status of interest which can shed light on the extent to which education meets some of industry's needs is that of student. Table 10 displays the frequencies of individuals reporting to be students or apprentices and interns in a country. It shows that apprenticeship programs are important in Germany, the Netherlands and Denmark, and thus confirms anecdotal evidence. Similarly, the Skill Outlook 2015 reports that, the highest percentage of individuals under the age of 29 who are in secondary vocational education and apprentices are registered in Australia, Austria, Denmark, Germany and the Netherlands - though the identification of apprentices in the Outlook hinges on one extra variable besides the subjective status.⁴⁵ In the overall sample, however, only 0.8 or 0.6 percent of employment are apprentices (subjective status vs Skill Outlook definition), a much lower proportion.⁴⁶ Insofar as apprentices provide an answer to the training section of the survey, they are included in the main estimates proposed above.⁴⁷ Between 88 and 93 percent of the individuals in apprenticeship and internship (subjective status vs Skill Outlook definition) also report to be engaging in formal training.

Table 9. Self-reported status, % respondents reporting to be a student, apprentice or intern.

	Student	Apprentice, Intern		Student	Apprentice, Intern
AUS	4.16%	1.30%	GBR**	2.35%	0.39%
AUT	3.01%	1.88%	IRL	2.58%	0.34%
BEL*	1.06%	0.21%	ITA	0.39%	0.36%
CAN	5.08%	0.59%	JPN	2.60%	0.03%
CZE	1.00%	0.04%	KOR	1.16%	0.36%
DEU	3.46%	3.53%	NLD	6.86%	2.27%
DNK	8.51%	2.08%	NOR	6.71%	1.28%
ESP	0.92%	0.38%	POL	1.39%	0.46%
EST	2.56%	0.28%	SVK	0.59%	0.04%
FIN	5.05%	0.60%	SWE	4.01%	0.23%
FRA	0.80%	1.06%	USA	3.31%	0.30%

Source: authors' own calculations based on PIAAC, * PIAAC data from Belgium only cover Flanders. **PIAAC data from the UK only cover England and Northern Ireland. For the frequency of other self-reported status categories, see Annex 3, Table A9.

44. The residual category "Other (status)" is neither straight-forward to interpret nor relevant, given the very low percentage it accounts for.
45. The Skill Outlook 2015 identifies apprentice workers using both the mentioned subjective status question, and information on the type of contract the individual is subject to (question *d_q09*, answer "apprenticeship or internship").
46. Apprentices whose official employment status is unemployed or out of the labour force are not included in the sample. The figures for Germany, Denmark and the Netherlands are, respectively, 4.1, 2.9 and 2.8 percent of the country's employment (reweighted frequencies).
47. The inclusion of apprenticeship into formal education during interviews was left to countries conventions, which can contribute to explain the 7 percent of apprentices who did not report to be in formal training. The list of countries for which this was the case is not available to the authors of the present study.

Table 10 also highlights that approximately 3 percent of the employees consider themselves principally students. Such percentages are especially high in the U.S., Germany, Sweden, Australia, Finland, Canada, Norway, the Netherlands and Denmark and may reflect the answers of working students or company-paid MBA students - training which does qualify as industry-specific investment. They may nevertheless also reflect measurement error, whereby individuals are mistakenly classified as being employees. This being the case, such observations should be dropped from the analysis, as they would not contribute to production.⁴⁸

Further descriptive analysis, however, supports the view of keeping these individuals in the analysis. If it is true that close to 100% of the respondents considering themselves students are engaged in formal training, 96% of them also report to be doing informal learning, and 56% of them to be doing on-the-job training. As a consequence, their subjective status of students does not imply that they do not represent industry-specific investment in training, as they are clearly involved in other company-based (training) activities.

Main findings and future work

The present work contributes to the long-term KBC measurement agenda, and in particular tries to address the measurement of challenging assets such as economic competencies. It focuses on human capital in particular, defined as the set of knowledge and skills obtained through schooling, training and every day experience that are useful in the production of goods, services and further knowledge (de la Fuente and Ciccone, 2003), and on workforce training in particular. It proposes a new methodology to estimate investment in training at the industry and country level for the years 2011-2012, mainly based on new survey data (PIAAC) collected at the individual worker level by the OECD for twenty two countries.

Human capital is a complex and multi-faceted economic phenomenon, which has received relatively little attention in recent years, at least as far as its measurement is concerned. As a consequence, this paper improves on the current status of the literature by investigating several dimensions of human capital related to firm-based training. It does so by moving beyond a one-dimension approach to training, by taking into account formal and on-the-job training, and informal learning. Furthermore, it stresses the role of industry heterogeneity in shaping investment in training, through both the frequency of training and its cost.

This methodology looks at training of employees and self-employed individuals from the perspective of the expenses incurred to improve the employee's human capital, rather than in terms of the output or productivity increase engendered by training. Doing so, it follows in the steps of an established literature on the measurement of knowledge based assets in general (e.g. Corrado et al. 2014) and of human capital in particular (e.g. O'Mahony, 2012), and their expenditure-based approaches.

The present methodology takes into account three different types of training, adding investment in formal training and informal learning to estimates of on-the-job training, which is usually the sole focus of the literature (mainly in light of data constraints). The estimates proposed here take into account both the direct cost and the opportunity cost of training, where the latter refers to the foregone earnings of workers and the foregone output of production when the individual is in training. The training activity considered in

48. A closer inspection suggests that students represent 21 percent of individuals reporting to be engaged in formal training. While these numbers remain marginal for the purpose of the present work, they might deserve further investigation in the future, especially in the context of studies addressing the working status of students.

the estimation is allowed to take place either during or outside working hours, and can be funded by either the employee or the employer, where these features impact the proportion of expenditure in training which can be treated as investment.

This work finds that most surveyed individuals in PIAAC receive at least some training, with proportions that vary considerably with the type of training: while almost every worker is the recipient of some informal learning, formal training is much less frequent (10-20% of employment). Evidence also suggests that low-skill individuals participate much less in training than medium- or high-skill individuals, pointing to a complementarity between skills and training.

When focusing on the measurement of investment in training, a higher degree of country heterogeneity emerges, with Australia, Denmark, the Netherlands, Canada and the UK investing substantially more as a percentage of GVA than the other countries with the same pattern being displayed by on-the-job training as well.

Investment in formal training, while found to be much less frequent, represents a sizeable share of total investment in training (20 to 60%, 44% on average across country). Conversely informal learning, which is found to be affecting almost all workers, makes up a much smaller percentage of investment in training (10 to 30%) across industries and countries. There is substantial sector heterogeneity in the relative importance of formal training, on-the-job training and informal learning investment, especially when comparing figures across countries. Investment in on-the-job training is on average more relevant in business services than in production (with the exception of Australia), while public services seem to be more intensive in investment in formal training than other sectors.

Overall the figures proposed suggest on-the-job training to be relatively more important in advanced services activities such as professional and business services, as well as in public-oriented services such as education and health services. These appear very intensive in formal training too, and future analysis might shed light on the drivers of such a pattern. Estimates seem to be broadly consistent with two key references in the literature as far as on-the-job training is concerned. Furthermore, they are robust to changes in the methodology, in particular with respect to the way in which p and q are computed, and the use of the self-reported work status of the individuals in PIAAC.

Future work will try to refine the current analysis and to propose capital figures, with the end goal to address a wide array of policy relevant questions including the contribution of investment in KBC, especially organisational capital and training, to labour productivity; and the role of investment in KBC for participation and positioning in global value chains.

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ANNEX 1

This Annex reports all questions which were exploited in the methodological section of this study.

- **FE12:** “Did you attend any formal training activity in 12 previous months?” (*Yes/No*). Derived variable .
- **B_Q02B:** “What is the level of the qualification you are currently studying for?” (*choose one of 6 ISCED categories*)
- **B_Q04A:** “During the last 12 months, have you studied for any formal qualification, either full-time or part-time?” (*Yes / No*)
- **B_Q05A:** (in reference to question B_Q04A) “What was the level of this qualification?” (*choose one of 6 ISCED categories*)
- **B_Q10A:** “In the last 12 months, while studying for this qualification, were you employed at any time, either full-time or part-time? (*Yes / No*)
- **B_Q10B:** (in reference to question B_Q10A) “Did this study take place..? (*Only during working hours; Mostly during working hours; Mostly outside working hours; Only outside working hours*)
- **B_Q10C:** (in reference to question B_Q10A) “How useful were your studies for this qualification for the job or business you had at that time? Would you say they were” (*Not useful at all; Somewhat useful; Moderately useful; Very useful*)
- **B_Q11:** (in reference to question B_Q10A) “Did an employer or prospective employer pay for tuition or registration, exam fees, expenses for books or other costs associated with your studying for this qualification?” (*Yes, totally; Yes, partly; No, not at all; There were no such costs; No employer or prospective employer at that time*)
- **NFE12:** “Did you attend any non-formal training activity in 12 previous months?” (*Yes/No*). Derived variable.
- **B_Q15B:** (in reference to variable NFE12) “Did this study take place?” (*Only during working hours; Mostly during working hours; Mostly outside working hours; Only outside working hours*)
- **B_Q15C:** (in reference to variable NFE12) “How useful was this training for the job or business you had at that time or still have? Would you say it was” (*Not useful at all; Somewhat useful; Moderately useful; Very useful*)
- **B_Q16:** (in reference to variable NFE12) “Did an employer or prospective employer pay for tuition or registration, exam fees, expenses for books or other costs resulting from your participation in this activity? Would that be” (*Yes, totally; Yes, partly; No, not at all; There were no such costs; No employer or prospective employer at that time*)
- **B_Q17:** (in reference to variable NFE12) “Now let’s look at the total amount of time you have spent in the past 12 months on all types of courses, training, private lessons, seminars or workshops. What is the easiest way to describe the total time you spent on all these activities: would that be in whole weeks, in whole days or in hours? Exclude time spent on homework or travel.” (*Weeks; Days; Hours*)
- **B_Q18A, B_Q19A, B_Q20A:** “How many whole (weeks; days; hours) did you spend in these activities?” (*Number*)
- **C_Q07:** “Please look at this card and tell me which ONE of the statements best describes your current situation.” (*Full-time employed; Part-time employed; Unemployed; Pupil, student; Apprentice, internship; In retirement or early retirement; Permanently disabled; In compulsory military or community service; Fulfilling domestic tasks or looking after children/family; Other*)
- **D_Q03:** “In which sector of the economy do you work?” (*Private sector; Public sector; Non-profit organisation*)

- **D_Q06A:** “How many people work for your employer at the place where you work? Would that be” (*1-10 people; 11-50; 51-250; 251-1000; more than 1000 people*)
- **D_Q07A:** “Do you have employees working for you? Please include family members working paid or unpaid in the business.” (*Yes/No*)
- **D_Q07B:** “How many people do you employ? Would that be” (*1-10 people; 11-50; 51-250; 251-1000; more than 1000 people*)
- **D_Q09:** “What kind of employment contract do you have?” (*Indefinite; Fixed term; Temporary employment agency contract; Apprenticeship or other training scheme; No contract*)
- **D_Q10:** “How many hours do you usually work per week in this job? Include any usual paid or unpaid overtime, but exclude lunch breaks or other breaks.” (*Number of hours*)
- **D_Q13A:** “In your own job, how often do you learn new work-related things from co-workers or supervisors?” (*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*)
- **D_Q13B:** “How often does your job involve learning-by-doing from the tasks you perform?” (*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*)
- **D_Q13C:** “How often does your job involve keeping up to date with new products or services?” (*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*)

ANNEX 2

1) Comparing total employment in PIAAC and LFS

Table A1: PIAAC and LFS total employment, 15 EU countries

Country	PIAAC	LFS	Calibration year	Difference (%)
AUT	2554474	2613100	2011	-2.2%
CYP	199955	259900	2011	-23.1%
CZE	3145317	3220100	2011	-2.3%
DEU	23371411	23252100	2010	0.5%
DNK	1523105	1521700	2011	0.1%
ESP	12516523	12264200	2012	2.1%
EST	391018	363300	2012	7.6%
FIN	1418074	1417700	2011	0.0%
FRA	16112170	16505000	2012	-2.4%
IRL	1191322	1217000	2011	-2.1%
ITA	15449723	15727900	2010	-1.8%
NLD	4791550	4756200	2011-2012	0.7%
POL	10790046	10233800	2011	5.4%
SVK	1558975	1565000	2011	-0.4%
SWE	2528799	2639200	2011	-4.2%

Source: PIAAC survey and Eurostat's LFS data. In grey, countries for which the difference between LFS and PIAAC is greater than 5%.

Table A2: Finland (2011) employment by economic activity, PIAAC and LFS.

ISIC	Description	PIAAC	LFS	Difference (%)
A	Agriculture, forestry, fishing	37034	46400	-20.2%
B	Mining and quarrying	4274	3500	22.1%
C	Manufacturing	218988	216100	1.3%
D	Electricity, gas, steam and air conditioning supply	10212	7100	43.8%
E	Water supply; sewerage, waste management and remediation activities	7793	6100	27.7%
F	Construction	101086	99900	1.2%
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	177994	175800	1.2%
H	Transportation and storage	87798	83200	5.5%
I	Accommodation and food service activities	33851	40500	-16.4%
J	Information and communication	61320	72300	-15.2%
K	Financial and insurance activities	20658	33300	-38.0%
L	Real estate activities	6313	11100	-43.1%
M	Professional, scientific and technical activities	99795	98600	1.2%
N	Administrative and support service activities	59456	48800	21.8%
O	Public administration and defence; compulsory social security	71709	69600	3.0%
P	Education	118353	107900	9.7%
Q	Human health and social work activities	207924	218900	-5.0%
R	Arts, entertainment and recreation	37065	31600	17.3%
S	Other service activities	48441	39700	22.0%
T	Activities of households as employers; undifferentiated goods and services producing activities of households for own use	6702	2400	179.3%
U	Activities of extraterritorial organizations and bodies	1307	0	NA
No response	No response	0	4900	-100.0%

Source: PIAAC survey and Eurostat's LFS data. In grey, industries for which the difference between LFS and PIAAC employment exceeds 25% of the latter.

2) Estimation of the average number of hours per day spent in informal learning

The objective of this section is to provide an estimates of hours per day employees spend in training, on the basis of Loewenstein and Spletzer (2000) for the U.S., Kurosawa (2001) for Japan, and Nelen and de Grip (2009) for the Netherlands. These papers report different estimates of the length of training in a year, which are here made comparable. In particular, both Loewenstein and Spletzer (2000) and Kurosawa (2001) distinguish between newly hired employees and all other employees. Loewenstein and Spletzer (2000), however, report the length of training in number of hours per year, Kurosawa (2001) does so in days per year, while Nelen and de Grip do so in hours per week. These figures are reported in the first three rows of Table A3, in bold.

The number of hours of informal learning per day for the U.S. is then obtained by dividing the number of hours per year (*Hours/Year*) by the average number of working days in 1993 and 1994 (250.5, not reported in Table A3). For Japan, the number of days per year is transformed in hours per year using *Working Hours/Day*, then divided by the number of working days in 1994 (248, not reported in Table A3). Finally, for the Netherlands, the number of hours of training per week (*Hours/Week*) is divided by the average number of working hours in a week as reported in the Life Long Learning survey used by Nelen and de Grip (2009) (i.e. 41.9); the result is then multiplied by the number of hours actually worked in a day (*Working Hours/Day*).

Table A3: Average number of hours per day spent in informal learning, country comparisons.

	US (1993-94)				Japan (1994)		Netherlands (2007)
	Newly Hired		Others		Newly Hired	Others	Full Time N
	Supervisor	Co-worker	Supervisor	Co-worker	Total	Total	Total
<i>Days/Year</i>					28.7	12.5	
<i>Hours/Year</i>	49.8	78.4	22	30.9			
<i>Hours/Week</i>							11.9
<i>Working Hours/Day</i>	7.3	7.3	7.3	7.3	7.7	7.7	5.6
<i>Hours/Day</i>	0.20	0.31	0.09	0.12	0.89	0.39	1.56

Source: Loewenstein and Spletzer (2000) for the U.S., Kurosawa (2001) for Japan, and Nelen and de Grip (2009) for the Netherlands. The numbers in bold are taken from these articles directly and elaborated by the authors for the present study, yielding the remaining figures which populate the table. The number of working hours per day is calculated from the average hours worked per employee ("Total Employment") in the reference year, from the OECD. The figures for the U.S. are averaged between 1993 and 1994, as in Loewenstein and Spletzer (2000).

3) Constructing the ratio of direct to opportunity cost of on-the-job training by industry and firm size for non-CVTS countries.

This section reports the results of taking the ratio between the (industry- or size-) average direct cost of on-the-job training, over the average labour cost of on-the-job training (i.e. the compensation of employees receiving the training) as reported in the CVT Survey, round 4.

The tables display a high degree of variability in the ratio across industries and firm sizes, reflecting different propensities to offer training as well as different average cost of training along these dimensions (for instance, due to economies of scale and frequency of outsourcing of training). However, these ratios also vary considerably across country. This information limits the possibility to exploit these ratios to approximate the direct cost of on-the-job training for those countries which are not covered by the CVT survey.

Table A4: Ratio of direct and labour costs per training hour (in Purchasing Power Standards), by industry

Country/Industry	TOTAL	B-E	F	G-I	J-K	L-N, R, S
AT	1.20	1.23	1.04	1.52	1.31	0.94
BE	0.58	0.67	0.45	0.75	0.64	0.33
CY	0.59	1.00	1.76	1.50	0.31	0.56
CZ	1.07	1.00	1.00	1.15	1.05	1.21
DE	1.06	0.69	1.08	2.09	1.09	n.a.
DK	0.70	0.48	0.18	1.00	0.71	1.08
EE	0.86	0.92	0.71	1.31	0.59	1.08
ES	0.63	0.63	0.55	0.58	0.77	0.63
FI	1.13	1.23	0.65	1.19	1.21	0.86
FR	1.11	0.97	1.23	1.32	0.91	1.15
IT	0.45	0.61	0.80	0.52	0.33	0.50
NL	1.11	1.14	1.13	0.76	1.70	1.07
NO	0.66	0.76	0.73	0.73	0.61	0.54
PL	1.00	0.88	1.00	0.92	0.90	1.40
SE	1.21	1.18	2.86	1.11	0.94	1.04
SK	0.94	0.93	0.88	1.29	0.95	0.73
UK	1.62	1.85	1.77	1.25	1.71	2.08
EU28	0.96	0.82	1.10	1.14	0.91	1.00
Mean	0.94	0.95	1.05	1.12	0.93	0.95
Median	1.00	0.93	1.00	1.15	0.91	0.99
SD	0.30	0.32	0.62	0.40	0.40	0.43
Min	0.45	0.48	0.18	0.52	0.31	0.33
Max	1.62	1.85	2.86	2.09	1.71	2.08

Source: Continuous Vocational Training Survey (2010) and authors' calculations. The difference is calculated as (PIAAC-LFS)/LFS.

Table A5: Ratio of direct and labour costs per training hour (in Purchasing Power Standards), by firm size

Country/Size	Total	10-49	50-249	>250
AT	1.20	1.39	0.94	1.39
BE	0.58	0.60	0.49	0.63
CY	0.59	1.12	0.33	0.68
CZ	1.07	1.27	1.23	0.94
DE	1.06	1.71	1.04	1.00
DK	0.70	0.67	0.52	0.85
EE	0.86	1.36	1.23	0.50
ES	0.63	0.57	0.59	0.69
FI	1.13	1.19	1.12	1.08
FR	1.11	0.96	1.16	1.14
IT	0.45	0.92	0.60	0.36
NL	1.11	0.90	1.00	1.21
NO	0.66	0.82	0.52	0.67
PL	1.00	1.20	1.31	0.82
SE	1.21	1.04	1.41	1.20
SK	0.94	1.35	1.00	0.81
UK	1.62	1.93	1.40	1.58
EU28	0.96	1.09	0.96	0.93
Mean	0.94	1.12	0.93	0.92
Median	1.00	1.12	1.00	0.85
SD	0.30	0.37	0.35	0.32
Min	0.45	0.57	0.33	0.36
Max	1.62	1.93	1.41	1.58

Source: Continuous Vocational Training Survey (2010) and authors' calculations. The difference is calculated as (PIAAC-LFS)/LFS.

4) Constructing a measure of direct cost of on-the-job training for non-CVT countries

The direct cost of training is taken for European countries (except for Ireland) from the CVT Survey for 2010. For the other countries covered by the present study but not by the CVTS (Australia, Canada, Ireland, Japan, Korea, and the U.S.), this study takes the average of the direct cost reported by European countries which fall in the same cluster as the non –CVTS countries. The clusters are constructed based on the variables contained in Table A6.

Table A6: Variables used in the cluster analysis and related sources.

Variables	Source
Country level	
GDP per capita	OECD National Accounts
Education expenditures/GDP	OECD Education at a glance
Share of private expenditures on total educational expenditures	OECD Education at a glance
Share of population attaining tertiary education	OECD Education at a glance
Participation rate, by gender	OECD Annual LFS
Employment rate, by gender	OECD Annual LFS
Unemployment rate	OECD Annual LFS
Youth unemployment rate	OECD Annual LFS
Incidence of part time work, by gender	OECD
Employment protection legislature index	OECD
Industry level (5 categories)	
Average job tenure	PIAAC
Average weekly hours worked	PIAAC
Average age of employees	PIAAC
Modal education level	PIAAC
Average duration of on-the-job training	PIAAC
Average time spent in on-the-job training	PIAAC
Incidence of on-the-job training	PIAAC
Incidence of formal training	PIAAC
Incidence of informal learning	PIAAC
Share of industry value added in total economy	OECD National Accounts and Eurostat
Share of industry employment in hours in total economy	OECD National Accounts
Share of employment by size class	OECD Entrepreneurship at a glance
Number of firms by industry (3 categories) and size (3 categories)	OECD Entrepreneurship at a glance
Industry / economy average hourly wage	OECD National Accounts and ILOSTAT

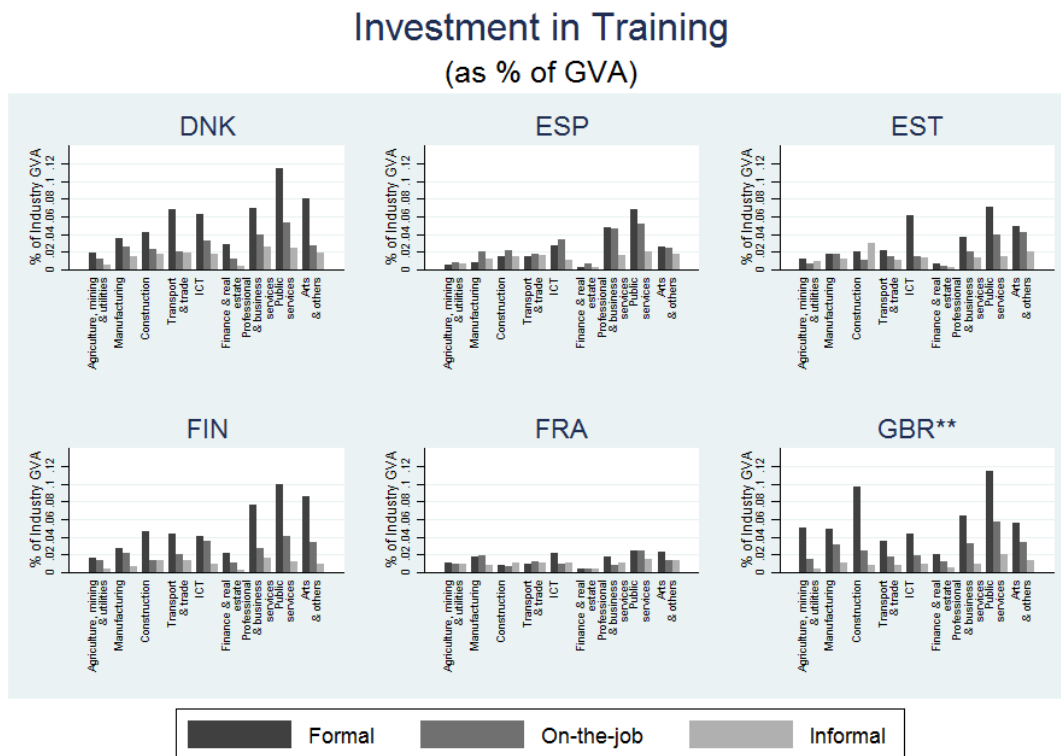
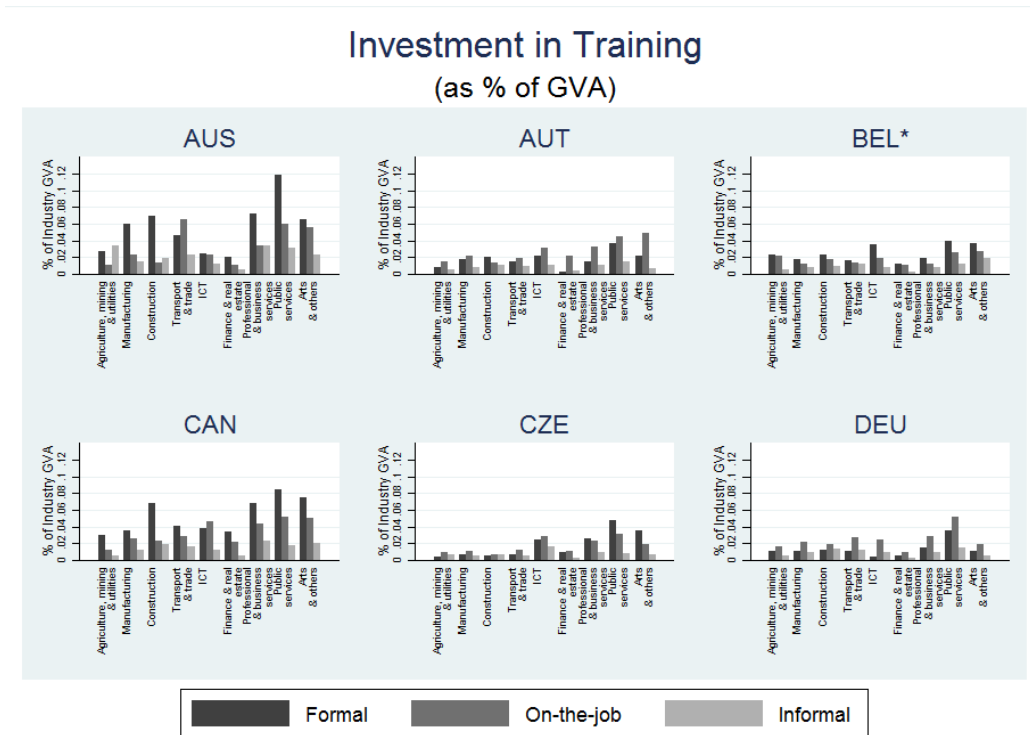
Based on the Duda and Hart criterion (Duda, Hart, and Storck, 2001), the optimal number of clusters to be used is eight. The resulting clusters are reported in Table A5. In practice, with eight clusters one of the countries for which there is no information in the CVTS (Australia) would be self-standing. This study thus exploits the second-best clustering specification, which signals the existence of seven clusters, all of which are identical to the eight-digit specification, except for the one including Australia, which is grouped together with Sweden and Denmark in the seven-cluster specification.

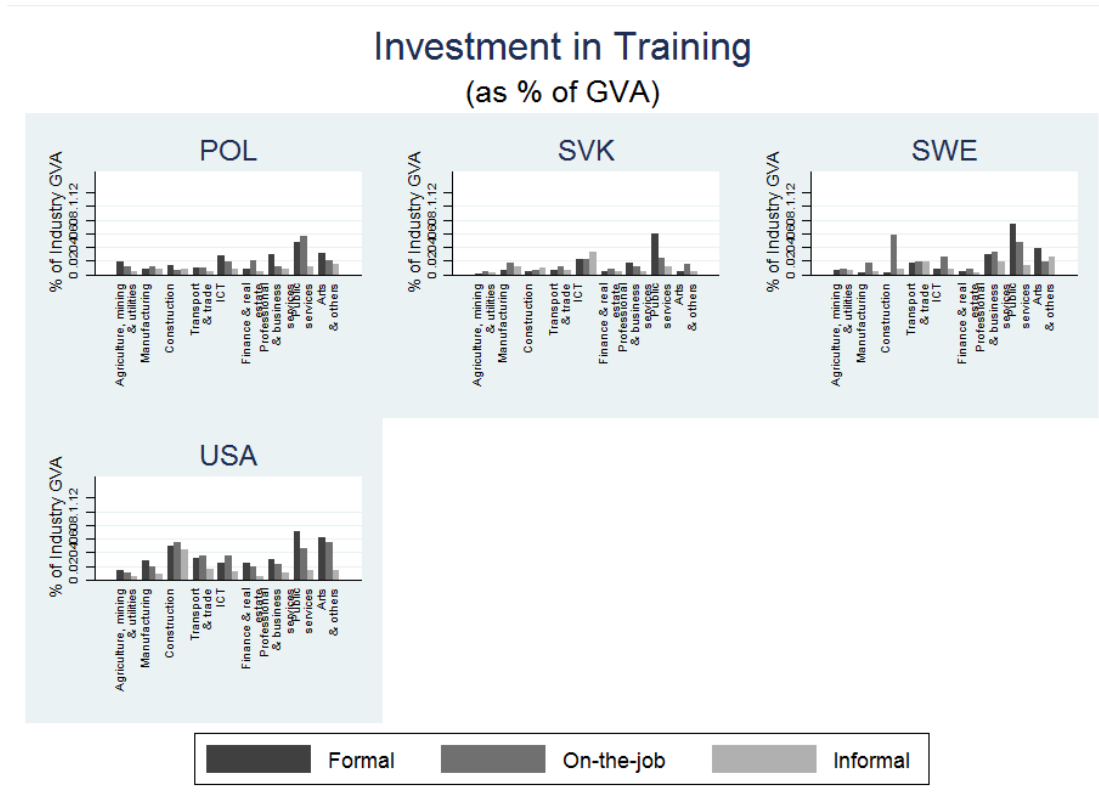
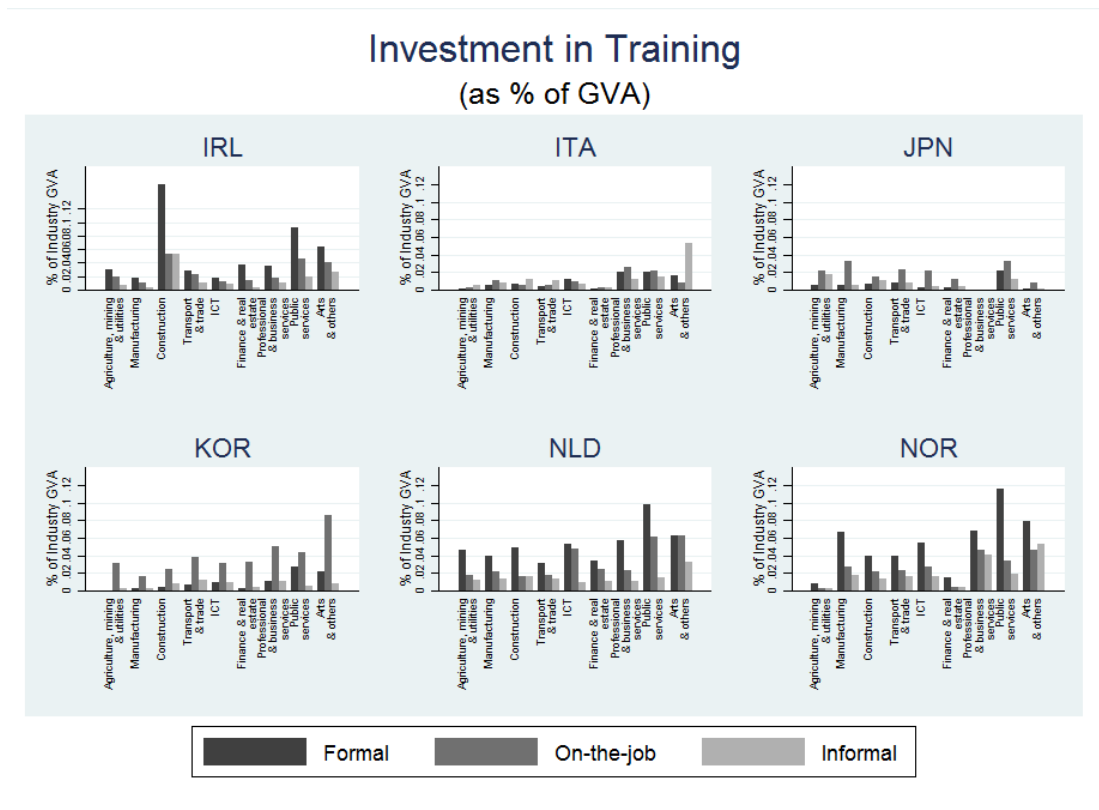
Table A7: Outcome of the clustering analysis

	Countries – 8 clusters	Countries – 7 clusters
Cluster 1	AUT, CAN, FIN, IRL, NLD, USA	AUT, CAN, FIN, IRL, NLD, USA
Cluster 2	BEL, FRA, DEU, JPN	BEL, FRA, DEU, JPN
Cluster 3	NOR	NOR
Cluster 4	CZE, EST, POL, SVK	CZE, EST, POL, SVK
Cluster 5	ITA, GBR	ITA, GBR
Cluster 6	KOR, ESP	KOR, ESP
Cluster 7	DNK, SWE	AUS, DNK, SWE
Cluster 8	AUS	

Sources: various databases (as in Table A6) and authors' calculations

ANNEX 3: FURTHER RESULTS





* PIAAC data from Belgium only cover Flanders. **PIAAC data from the UK only cover England and Northern Ireland.

Table A9: Self-reported status, frequency by country and status.

	<i>Full-time employed</i>	<i>Part-time employed</i>	<i>Unemployed</i>	<i>Student</i>	<i>Apprentice or intern</i>	<i>Retiree</i>	<i>Disabled</i>	<i>Military</i>	<i>Domestic tasks</i>	<i>Other</i>
AUS	66.30%	22.91%	0.61%	4.16%	1.30%	0.33%	0.00%	0.00%	1.71%	2.67%
AUT	70.14%	20.00%	0.51%	3.01%	1.88%	0.82%	0.07%	0.21%	2.31%	1.04%
BEL*	72.40%	24.33%	0.36%	1.06%	0.21%	0.52%	0.16%	0.00%	0.21%	0.76%
CAN	71.64%	16.47%	2.23%	5.08%	0.59%	0.66%	0.18%	0.06%	1.00%	2.10%
CZE	88.62%	5.85%	1.15%	1.00%	0.04%	0.93%	0.20%	0.00%	1.63%	0.59%
DEU	65.32%	22.56%	0.62%	3.46%	3.53%	1.10%	0.34%	0.24%	1.20%	1.64%
DNK	69.96%	15.16%	1.11%	8.51%	2.08%	0.78%	0.10%	0.00%	0.44%	1.85%
ESP	78.30%	14.47%	3.53%	0.92%	0.38%	0.30%	0.14%	0.00%	0.75%	1.22%
EST	84.02%	7.34%	1.27%	2.56%	0.28%	0.64%	0.37%	0.08%	2.21%	1.24%
FIN	79.67%	9.04%	0.98%	5.05%	0.60%	0.82%	0.12%	0.05%	2.44%	1.23%
FRA	79.61%	15.74%	0.87%	0.80%	1.06%	0.84%	0.02%	0.00%	0.48%	0.58%
GBR**	71.96%	22.96%	0.38%	2.35%	0.39%	0.36%	0.08%	0.03%	0.50%	0.99%
IRL	71.26%	21.96%	1.53%	2.58%	0.34%	0.42%	0.17%	0.00%	0.82%	0.92%
ITA	78.97%	15.88%	1.39%	0.39%	0.36%	0.15%	0.06%	0.10%	0.36%	2.34%
JPN	71.41%	23.27%	0.31%	2.60%	0.03%	0.18%	0.14%	0.00%	1.14%	0.92%
KOR	82.79%	12.11%	0.62%	1.16%	0.36%	0.12%	0.04%	0.12%	1.34%	1.35%
NLD	52.98%	34.39%	0.47%	6.86%	2.27%	0.74%	0.11%	0.00%	1.04%	1.15%
NOR	74.10%	14.97%	0.43%	6.71%	1.28%	0.21%	0.91%	0.04%	0.65%	0.70%
POL	86.14%	5.82%	1.80%	1.39%	0.46%	1.45%	0.41%	0.00%	0.98%	1.54%
SVK	92.40%	3.98%	1.05%	0.59%	0.04%	0.57%	0.03%	0.61%	0.73%	0.00%
SWE	73.82%	18.69%	0.84%	4.01%	0.23%	0.68%	0.00%	0.00%	1.08%	0.65%
USA	76.70%	13.31%	1.77%	3.31%	0.30%	0.42%	0.27%	0.00%	0.86%	3.06%
Avg	75.39%	16.42%	1.08%	3.07%	0.82%	0.59%	0.18%	0.07%	1.09%	1.30%

Source: authors' own calculations based on PIAAC reweighted data, * PIAAC data from Belgium only cover Flanders. **PIAAC data from the UK only cover England and Northern Ireland.