Bank i Kredyt 51(1), 2020, 91-120

BANK I KREDYT
BANK & CREDIT

What fosters firm-level labour productivity in Eastern European and Central Asian countries?

Aleksandra Kordalska*, Magdalena Olczyk#

Submitted: 3 June 2019. Accepted: 25 November 2019.

Abstract

This study examines labour productivity performance and its determinants in Eastern European and Central Asian (EECA) firms using micro-level data. We find significant differences in labour productivity among members of the European Union in Eastern Europe and other Eastern European and Central Asian countries. We also confirm the important impact of foreign ownership, exporter status, and highly skilled workers on productivity levels. However, we reveal a non-linear relationship between firm age and labour productivity. Additionally, significant differences in labour productivity determinants between services and manufacturing are found. The productivity of service firms, unlike manufacturing firms, is much more sensitive to changes in productivity factors.

Keywords: Eastern Europe and Central Asia, firm-level analysis, labour productivity

JEL: C21, J24 O52, O53

* Gdańsk University of Technology, Faculty of Management and Economics; e-mail: aleksandra.kordalska@zie.pg.edu.pl.
# Gdańsk University of Technology, Faculty of Management and Economics; e-mail: magdalena.olczyk@zie.pg.gda.pl

1 Introduction

Two decades after the collapse of communist regimes, Eastern European and Central Asian (EECA)[1] countries are remarkably different. The differences are particularly large among the countries of Central and Eastern Europe (CEE). Advanced democratic welfare states in East-Central Europe have converged economically with the continental member states of the European Union (EU) (Lauzadyte--Tutliene, Balezentis, Goculenko 2018). The former Soviet republics (except the Baltic countries) tend to have authoritarian or hybrid regimes, higher levels of poverty and inequality, and much less generous welfare policies (Ekiert 2015). Countries in Southeast Europe are somewhere between these two groups, with some progress on many dimensions and significant stagnation in reforms (OECD 2016). In turn, the new Southeast European members of the EU, Bulgaria and Romania, tend to lag behind all the other EU countries in all important respects.

Despite many differences, EECA countries have one common feature according to the Transition Report prepared by the European Bank for Reconstruction and Development (EBRD 2017). They may be stuck in a "middle-income trap" and experience a slowdown in productivity growth at income levels between one-third and two-thirds that of the United States. Furthermore, in many economies in the EECA region, growth lags behind that of comparable middle-income countries elsewhere in the world. The most recent analysis, by Levenko, Oja and Staehr (2019), confirms that in CEE countries, after the global financial crisis, capital deepening and increased capital utilisation have contributed to economic growth in equal proportions, while growth in total factor productivity (TFP) has been virtually absent in most Central and Eastern European countries in this period. The lack of TFP growth is delaying the catch-up process and casts doubt on the ability of these countries to sustain growth without the increased use of resources (Vuegelers 2011). Having exhausted the advantages that underpinned their strong growth performance in the past – almost without exception, low-cost labour – the countries in the EECA region now require a new growth model to create sustained economic growth, focused on improving the productivity of individual firms, expanding infrastructure, and green growth. That is why research on the determinants of productivity in Eastern European and Central Asia have become more important.

Also, some empirical analyses show a large dispersion in firm productivity, which suggests that analysing total economic or industry average productivity will not give a full picture (Bartelsman, Doms 2000; Bartelsman, Haltiwanger, Scarpetta 2013; Dosi, Lechevalier, Secchi 2010). Syverson (2004) finds that, in the US manufacturing sector, firm productivity was on average 1.92 times higher in the 90th productivity percentile than the 10th one, implying that with the same inputs, firms in the 90th productivity percentile have nearly twice as much output as those in the 10th percentile. Using a harmonised cross-country firm-level database in EU countries, the CompNet Task Force (2014) also documents a large degree of heterogeneity in terms of firm productivity and size, both within and across countries. This is because countries, or industries within countries, might display the same productivity on average but have a very different underlying distribution (Papa, Rehill, O'Connor 2018). So, micro-data-based research on productivity is essential.

Studies on the determinants of labour productivity in EECA economies are relatively scarce mostly due to data limitations, i.e. the lack of available data. Only a few studies on this topic use a disaggregated firm-level approach, e.g. Botrić, Božić and Broz (2017) on post-transition economies.

[1] List of analysed Eastern European and Central Asian countries – see Table 6.

Additionally, the majority of these studies concentrate on analysing manufacturing productivity. This is connected with the belief that productivity is a vague, useless concept in the services industry, because service companies do not usually measure their success in terms of productivity (Dobmeier 2016). However, a marked reduction of the differences between the two sectors is observed. First, the environment in which service companies operate is becoming more like the industrial business environment: markets are becoming more competitive, the turnover rate is increasing, and the life cycle of services is becoming shorter (Balci, Hollmann, Rosenkranz 2011). Additionally, innovation in the services is becoming more like that in manufacturing, i.e. the distinction between 'hard' innovation in the industrial sector and 'soft', non-technological innovation in the service sector is very blurred.

Consequently, the aim of this analysis is to identify firm-specific factors which determine labour productivity of EECA countries and to determine their different role in sectoral and regional labour productivity growth. We want to add something new to the empirical literature on productivity in EECA countries by exploiting information from the fifth round of unique firm-level survey carried out by the EBRD and the World Bank (WB), called the Business Environment and Enterprise Performance Survey (BEEPS V). Due to a high degree of firm heterogeneity in our sample, we group factors which can potentially influence labour productivity into two sets. The first group relates to structural firm characteristics such as size, age, foreign ownership, being a part of larger company and the status of exporter. The second group of factors refers to firm activities and economic features of companies that may affect labour productivity such as an innovation activity, R&D expenditures, skills of workers and managers, ICT use and usage of technology licensed from a foreign-owned company. We formulate two main hypotheses:

H1: In labour productivity growth firm characteristics are as important as company activities connected with innovation, technology and employees qualifications.

H2: The determinants of productivity differ among sectors (especially between manufacturing and services) and among EECA countries (especially between Eastern European and Central Asian countries).

The rest of the paper is organised as follows. Section 2 provides a brief review of the literature on the main determinants of labour productivity. In section 3 a research strategy is presented. Section 4 gives an overview of our data and methodology. Section 5 looks at the survey results on labour productivity, focusing on the empirical models and the discussion of results. Section 6 concludes and offers some policy recommendations.

2 Theoretical background and related empirical studies

In a survey of the literature, Syverson (2011) divided inter-firm differences in productivity into two broad categories. The first group consists of factors within the firm, such as managerial talent, the quality of labour and capital inputs, product innovation, and the organisational structure of the firm's production units. The second group is made up of environmental determinants, such as productivity spillovers from knowledge transfers, the degree of competition in labour and product markets, and the impact of regulation. Some studies document complementarities between the two groups. For instance, strong competition and flexible labour markets allow firms to adopt better human resource management practices (Bloom et al. 2012). In our paper, we propose to divide them into two subgroups:

factors connected with enterprise characteristics (e.g. age or size) and those related to firm economic activity (e.g. their innovation level or technological capability).

The growing literature on firm heterogeneity shows a massive dispersion in firm outcomes, such as revenue, employment, and TFP (Bernard et al. 2019; Syverson 2011). It draws attention to the role of individual firm characteristics in explaining some economic phenomena. All begins with Melitz's model (2003), which underlines the role in productivity growth of 'being an exporter', but other papers indicate the importance of other firm-specific features, such as productivity determinants (Aiello, Ricotta 2016; Sangho 2018).

The first is firm size. The literature has established that small firms are less productive than large firms, especially because of scale economies (larger firms may have lower average and marginal costs). A positive relationship between firm size and labour/TFP is found in several studies, i.e. Leung, Césaire and Terajima (2008) on Canadian firms, Du and Temouri (2015) on UK enterprises, and Cieślik, Gauger and Michałek (2017) on Ukrainian companies. However, in Moral-Benito (2016), Spanish firm size shocks are not followed by productivity gains at the firm level. Accordingly, our paper tests the following hypothesis:

H1: Firm size is expected to have a positive effect on labour productivity.

Second, among various firm-specific factors influencing productivity, firm age is important. Coad, Segarra and Teruel (2013) have three theoretical predictions on how firm age affects firm productivity positively or negatively: selection effects, learning-by-doing effects, and inertia effects. Selection pressures result in an increase in the average productivity level of surviving firms, even if the productivity levels of individual firms do not change with age (Jovanovic 1982). Learning-by-doing effects occur when firms increase their productivity as they learn about more productive production techniques and incorporate these improvements into their production routines (Arrow 1962; Vassilakis 2008). Inertia effects indicate that as firms get older, they might become less productive if they become increasingly inert and inflexible. When firms grow older, they become very bureaucratic, with less organisational flexibility and ability to change rapidly (Barron, West, Hannan 994; Hannan, Freeman 1984). So in the first period of the company's maturity, its age can positively influence the productivity achieved (via selection and learning effects), but after the enterprise reaches maturity, its age may weaken its performance in terms of productivity (via inertia and learning effects).

Previous studies on the relationship between firm age and enterprise productivity may indicate the nonlinear character of this relationship. Generally, firm age is positively related to productive growth, as shown in recent analyses of Czech (IMF 2018) or Ethiopian (Legesse 2018) firms, but 'the size premia' for productivity are significantly weaker in the service sector than in manufacturing (Berlingieri, Calligaris, Criscuolo 2018). Simultaneously, we find strong evidence in Australian (Palangkaraya, Yong, Stierwald 2009), Spanish (Coad, Segarra, Teruel 2013), and Croatian (Pervan, Pervan, Ćurak 2017) enterprises of a high degree of inertia in terms of productivity: older firms on average are less productive, as the benefits of their cumulative knowledge on all crucial aspects of the business are overcome with their inertia, inflexibility, and ossification due to the accumulated rules, routines, and organisational structure. In view of these different relationships between age and productivity, we propose the following hypothesis:

H2: Firm age needs to be controlled for when looking at relationships between factors that affect labour productivity, as a nonlinear relationship may exist between firm age and labour productivity.

Another characteristic of many companies, i.e. being part of a large firm may also affect productivity. In the literature it is often related to the ownership advantages of transnational corporations, which provide local affiliates with two benefits (Nguyen, Nishijima 2009; Srinivasan, Archana 2011). First, access to their better marketing connections and know-how of parent companies enable the use of scale economies. Second, access to parent companies' cumulative learning experience as well as access to sophisticated technologies and management experience improve technical efficiency. All this could have a positive influence on the labour productivity of enterprises, so we propose the following hypothesis:

H3: Being a part of larger firm is positively related to labour productivity growth.

Some studies on firm-specific determinants of firm performance indicate that foreign ownership participation increases firm performance (Greenaway, Guariglia, Yu 2014; Javorcik 2004). In the literature, we found strong evidence that foreign-owned firms are more productive than domestic firms in analyses by Guadalupe, Kuzmina and Thomas (2012) and Blonigen et al. (2012) on Spain, Weche-Gelübcke (2013) on Germany, Waldkirch (2014) on 118 developing countries, and Koch and Smolka (2017) on Austria. This is because foreign-owned firms invest more in R&D, are more likely to innovate (introduce new products and/or processes) than their domestic counterparts, and may be better managed (Haldane 2017). Driffield, Sun and Temouri (2018) analysing a large firm-level dataset on Germany, Poland, Italy, and the UK and using an endogenous threshold approach shows significant differences and some non-linearities in the relationship between foreign ownership and productivity. These considerations lead us to propose the following hypothesis:

H4: Foreign-owned firms are more productive than domestic firms.

The last firm-specific feature considered as productivity determinant is a firm's status as an exporter. This is connected with the learning-by-exporting (LBE) hypothesis stipulated by Alvarez and Lopez (2005) that firms increase their productivity as a consequence of exporting. According to this hypothesis, the productivity-increasing effect of a firm's international activity is a consequence of, for example, increased competition from the larger international market and knowledge and expertise related to the foreign market, which non-exporters do not possess (Silva, Afonso, Africano 2012). In terms of LBE, some studies find a positive link between exporting and subsequent productivity growth (on Estonia, De Loecker 2013; on Japan, Hosono, Miyakawa, Takizawa 2015; on Spain, Manjon et al. 2013; on Germany, Schwarzer 2017). However, others find no evidence of such effects (on Latvia and Estonia, Benkovskis et al. 2017; on Germany, the UK, and France, Temouri, Vogel, Wagner 2013). The evidence for this effect so far is rather sparse, but the main factors that make it difficult to observe LBE are: the quick diffusion of all innovative solutions, which prevents enterprises from investing, and a relatively small share of exporters with little experience, among whom the effect is the strongest. Furthermore, supporting evidence suggests that LBE is far from guaranteed but, instead, is conditional on several factors. For example, it tends to occur more when firms export to developed economies (De Loecker 2007), or when they export many products to many destinations (Masso, Vahter 2015). According to Benkovskis et al. (2017), the occurrence of LBE can be conditional on the type of exporting activities. These arguments lead us to propose the following hypothesis:

H5: A firm's international activity may foster labour productivity.

Innovations are part of the second group of determinants, which may foster labour productivity of firms but are not related to firm characteristics. Measuring firm innovations is challenging. Many existing approaches focus on measuring inputs to innovation (e.g. R&D expenditures) or proxies for the output of innovation (e.g. patents), but such measures may capture only a fraction of a firm's innovative activity (Foster et al. 2018). Despite this, many studies show that R&D per employee or relative R&D intensity contribute to firm-level labour productivity growth across countries and sectors (on German enterprises, Baumann and Kritikos 2016; on the US and the EU, Castellani 2016; on China and India, Hecht 2018). Moreover, substantial empirical literature shows positive impacts of the output of innovations (product and process innovations) on labour productivity, but the impact of process innovation is more ambiguous (Hall 2011; Peters 2005). As mentioned earlier, the correlation between product innovation and productivity is often higher at larger firms, and as expected, in most countries the productivity effect of product innovation is larger in the manufacturing sector than in the services sector (OECD 2009). In view of the foregoing, we propose the following hypothesis:

H6: The level of innovativeness, measured by R&D expenditures or in terms of product/production/management/process/innovations, is positively correlated with labour productivity.

We also test how human capital determines labour productivity, based on the theoretical achievements of the 'new growth theories' (Lucas 1988; Romer 1986). In the literature, the four main effects of human capital impact on labour productivity are the worker effect (education increases the effective labour input from the hours worked), the allocative effect (better-educated workers are more effective at allocating available input factors to the production process), the diffusion effect (better-educated workers are more able to adapt to technological change and introduce new production techniques more quickly), and the research effect (higher education as an important input factor in R&D activities) (Cörvers 1997). Many empirical studies confirm the positive impact of highly skilled labour on the sector/firm labour productivity level, such as Rukumnuaykit and Pholphirul (2016) on Thailand, Bank of Malta (2018) on Malta, Sasso and Ritzen (2019) on 12 OECD economies and 17 industries, and Okumu and Mawejje (2019) on African firms. In addition to employee skills, the CEO's college degree, vocational training, and work experience are important for the increase in labour productivity growth. The results of the very large international survey of 10,000 organisations across 20 countries provide convincing evidence that the wide range in the quality of management practices explains differences in productivity among firms and countries, implying that better management leads to higher rates of growth and productivity (Bloom et al. 2012). Accordingly, we propose the following hypothesis:

H7: Higher levels of human capital, in terms of secondary-level educated workers or well-educated and experienced CEOs, are positively correlated with labour productivity growth.

The last group of labour productivity determinants is related to firms' technological capabilities. They are not only built by years of production experience but also require technologically advanced investment (Wignaraja 2012). Many technological activities are involved, but our research focuses on importing technology through foreign licences as an important factor in technology transfer and building internal capability (Wignaraja 2015). Many previous analyses show that technology imports have a significantly positive impact on labour productivity, in researches by OECD (2018) on Thailand, Fotros and Ahmadvan (2017) on Iran, and Youssef and Wei (2011) on China. Additionally, we want to check not only how technology imports but also how technology use influences firms' labour productivity. ICT (information, communication, and technology) use influences labour productivity through different channels. It improves access to information, helping firms to optimise management practices and reorganise their business model, to use their existing capacity more efficiently, and to reduce risks and costs (Bartel, Ichniowski, Shaw 2007). The literature highlights the role of necessary skills and modern organisational practices to obtain the productivity gains that ICT can provide (Bloom 2012). Previous studies suggest that ICT has a very strong positive impact on labour productivity, sometimes more than the other determinants (Ayodele et al. 2017; Cardona, Kretschmer, Strobel 2013; Nurmilaakso 2009; Oulton 2012), but this impact is greater in transition economies than in developed economies (Relich 2017). As a result of this discussion, we propose the following hypothesis:

H8: Enterprises that use ICT and foreign technology have higher labour productivity than other firms.

3 Research strategy

In this study, we examine the relationship between firm-level labour productivity (Y) and a set of selected determinants collected on individual enterprises. To evaluate this relationship empirically, we use a regression with two sets of explanatory variables which reflect firm characteristics (X) and firm activities (Z) respectively. Additionally, we explore whether the factors determining labour productivity vary across two groups of countries: Eastern EU countries and the other Eastern European and Central Asian countries and two groups of industries: manufacturing and services. We first examine this using binary variables (*EU, sector*) with the full sample. Our model takes the following form:

$$\ln Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 EU + \beta_4 sector + \varepsilon_i \tag{1}$$

In the next step, we focus on a regression estimated for sub-samples covering firms in Eastern EU countries and in the other EECA separately and then consider the manufacturing and service sectors separately.

The first estimator used in the regression is ordinary least squares (OLS). To evaluate the sensitivity of our results to changes in determinants that influence productivity, we estimate several specifications with alternative factors taken from a separate, specific group of variables Z as a robustness check.

In this study, we also consider the problem of potential endogeneity, which can appear especially when we test the LBE hypothesis and exports are used as an explanatory variable for labour productivity. This problem is widely discussed in the literature, mainly because of the interrelationship (reciprocal dependence) between productivity and exports (e.g. Feenstra, Kee 2008). Because of the sample limitations, in terms of both the cross-sectional dimension of our data instead of panel data and the lack of a reliable and highly correlated ‘proxy’ for exports at the level of disaggregation we use, we are forced to reject the usual approaches.

To address the problem of potential endogeneity of regressors, we use an instrumental variables (IV) estimation with heteroskedasticity-based instruments proposed by Lewbel (2012). Lewbel’s estimator utilises the heteroskedasticity of error terms to identify the structural parameters in a model with endogenous regressors if traditional identifying information, such as external instruments or repeated measurements, are absent. In our model, we use a modified two-stage least squares (2SLS) estimation based on this method.[2] The robustness check for 2SLS estimates is similar to that for OLS estimates.

[2] We employ the Stata routine ivreg2h (Baum, Schaffer 2012).

4 Data description and empirical model

The main database used in our empirical study is derived from the BEEPS V conducted by the EBRD and the WB. The survey provides a wide range of information at the firm level from 32 EECA countries. The database takes a form of cross-sectional data for 16,556 enterprises, between 2011 and 2016, with 62% of them evaluated in 2013. Detailed information about the database structure by country and by industry is presented in Table 6.

In our paper, firm-level labour productivity (ln*lprod*) is measured by the logarithm of the share of annual sales and the number of permanent full-time employees. To obtain the measure of firm-level productivity, first, we express firm sales in a common currency, US dollars. To do that, we convert firm sales with the aid of the WB market annual average exchange rates for particular years, and then we express all the values in 2013 constant prices.

Figure 1 illustrates the differences in labour productivity for EU and non-EU economies as well as for manufacturing and service sectors in both groups of countries. In all the graphs, the pattern of labour productivity distribution is similar, and the distributions for EU countries shift slightly to the right. On average, labour productivity in EU countries is always higher than in the rest of the sample, whether we analyse the full sample or particular sectoral groups. Additionally, two sample t-tests on the equality of means and on the equality of distribution are conducted. Both indicate significant differences across EU and non-EU economies as well as in the manufacturing and service industries in terms of labour productivity. All the results suggest that, in addition to relationships in the full sample, it is worth taking a closer look at the sub-samples to assess the discrepancies in productivity factors.

The equation for estimating labour productivity takes the following form:

$$\ln lprod_{ijc} = \beta_0 + \beta_1 X_{ijc} + \beta_2 Z_{ijc} + \beta_3 EU + \beta_4 sector + D_j + D_c + \varepsilon_{ijc} \tag{2}$$

As it is explained above, firm-level labour productivity (ln*lprod*) is measured by the logarithm of the share of annual sales and the number of permanent full-time employees, and is expressed in US dollars and 2013 constant prices.

The explanatory variables are divided into two main groups. A set of variables described by *X* consists of firm-level characteristics. The age of establishment (ln*age*) is measured by the logarithm of the difference between the year when the survey was conducted and the year when the firm began operations. Firm size (*size*) is a discrete variable that reflects whether the firm is micro, small, medium, or large, depending on the level of employment.[3] We also consider firm ownership, especially whether it has a foreign owner (*fowner*) as well as whether it is a part of a larger organisation (*partOFlarge*). The last factor in this group is linked to the firm's export performance. *Export* is a binary variable which takes a value of 1 if the share of exported products, both directly and indirectly,[4] in total sales is greater than 0.

[3] According to the BEEPS V database, micro firms employ fewer than 5 workers, small firms between 5 and 19, medium-size firms between 20 and 99, and large firms over 100 workers.

[4] In the BEEPS V questionnaire, indirect exports are understood as products that are sold domestically to third parties that then export them.

The second main group of variables *Z* reflects significant firm activities that may affect labour productivity. Those factors are divided into three sub-groups. In each sub-group we propose two measures which are used alternatively in different model specifications. The first sub-group illustrates the involvement of the firms analysed in different kinds of innovation – product, production, process, or management (*inno*) – as well as their R&D expenditure (*rd*). The second consists of binary variables that represent the firm's technology involvement. *Ftech* takes a value of 1 if the firm uses a technology licensed from a foreign-owned company, and *ICT* variable takes a value of 1 when the firm uses ICT tools. The third sub-group is variables which describe firm workers and their skills – i.e. in our model we use the number of workers with a university degree (*workerskills*) and the years of experience of top managers (*managerskills*). In further analysis, all specifications of model (2) which next to the firm's characteristics X contain the second group of variables Z, are called extended models.

Additionally, our model includes binary variables *EU* and *sector,* which allow us to observe the differences in labour productivity between Eastern EU countries and the other Eastern European and Asian countries and between manufacturing and service sectors respectively as seen in Figure 1. Finally, the model contains dummy variables to control for industry (D_j) and country (D_c) heterogeneity and random disturbance ε_{ijc}. Subscript *i* indicates firm, *j* describes industry and subscript *c* is for country.

Descriptive statistics for the total sample for both original and transformed variables are presented in Table 7. Table 8 contains descriptive statistics for Eastern EU member states and the other EECA countries, and for manufacturing and service sectors.[5] Table 9 includes the correlation matrix for all variables described above (for the total sample).[6] Additionally to fully describe our data, Figure 2 presents histograms of variables' distributions.

5 Empirical results and discussion

In this section, we present the results of estimating model (2). First, we analyse the model for the full sample, comprising more than 12,000 individual firms in 32 countries and 36 NACE 1.1 sectors (Table 1). Column (1) lists the OLS results for the base model with firm-level characteristics only and individual effects for industries and countries. In columns (2), (4), (6), and (8), we present the OLS results for an extended model that takes into account alternative measures of firm-level activities, as described earlier. Columns (3), (5), (7), and (9) report the same specifications, but the models are estimated with the IV method and heteroskedasticity-based instruments to control for potential endogeneity.

Regardless of the model specification and estimation method, we find evidence that firm ageing significantly influences labour productivity, but that relationship is parabolic rather than linear. In the first period of firm activity in a market, its productivity is supported by increasing experience and the 'learning-by-doing' effect, but as firm ages, their productivity drops because of increasing inertia and flexibility, as explained in the theoretical section of this paper.

Among other firm characteristics that foster increase in labour productivity is firm size. The larger the enterprise, the higher its labour productivity. That conclusion is in line with our expectations and confirms that the firms analysed achieve economies of scale. The positive and statistically significant

[5] Descriptive statistics for transformed variables (2SLS estimation with heteroskedasticity-based instruments) in terms of standard deviation, skewness and kurtosis are identical to standard deviation, skewness and kurtosis for original data (see Table 7). All descriptive statistics for transformed variables and for all sub-samples are available on request.

[6] Correlation matrices for all sub-samples are available on request.

link to productivity is also given by firm ownership expressed by foreign owner participation. Higher R&D expenditure, more innovation, or better management practices combined with foreign ownership positively affect firm productivity.

Considering firms' export status, we find a positive and significant impact on the phenomenon analysed, and at the same time it confirms the LBE hypothesis. The variable *export* is the sum of direct and indirect exports, so it suggests that linkages between domestic firms, the so-called domestic value chains, support an increase in labour productivity.

In this group of factors, the variable for which no significant influence is observed is *partOFlarge*, however the coefficients remain positive.

In our approach, to assess the sensitivity of the results to changes in data, we estimate different model specifications with the use of alternative variables within sub-groups of determinants. As mentioned earlier, we employ alternative measures of innovation, technology engagement, and human capital. Taking into account these measures of firm activity, we find strong and positive evidence for a relationship between firm-level labour productivity and different forms of innovation in which firms are involved, technology engagement linked to the use of ICT tools, and the use of technology delivered by foreign owners, as well as between productivity and the share of employees with a university degree (*workerskill*). Regardless of the model specification, the contribution of top managers' experience remains negligible. The impact of R&D activity is indeed positive, but it does not explain productivity in a significant way.

Our results indicate that firms in the Eastern EU and in manufacturing on average have higher labour productivity than those in other EECA countries and in services. It clearly suggests that individual regressions should be estimated for separate sub-samples.

On the basis of significant differences in labour productivity distribution (Figure 1) as confirmed by the results of tests for the equality of distributions and means, as well as bearing in mind the positive and significant *EU* coefficient in Table 1, we estimate equation (2) for Eastern EU countries and countries in Eastern Europe and Central Asia. The estimation results are presented in Tables 2 and 3. Columns (1)–(9) in both tables reflect analogous model specifications as described for Table 1, omitting only the *EU* variable.

A comparison of estimation results for the two separate groups of countries reveals important differences in the significance of particular factors and the level of their influence on labour productivity. Considering firm age, we confirm a non-linear pattern in the relationship as seen in a joint model. In the first period of activity in a market, EU firms generate higher levels of productivity than non-EU firms, and they do it more rapidly. At the same time, the decline in productivity with age takes place later at EU firms than at those from non-EU economies. Such significant differences can be explained as a result of non-EU countries having a less competitive market.

Discrepancies in coefficients are also visible when foreign ownership is taken into consideration. Enterprises in EU countries and those with foreign ownership on average have higher productivity than those with an exclusively domestic ownership (42–48%), whereas the average difference in labour productivity between foreign and domestically owned companies in non-EU countries is about 20–22%. We also note differences between Tables 2 and 3 in the significance of particular factors that influence productivity. Their impact still creates growth in the phenomenon, but firm size, widely understood innovations, and the use of foreign technology are not significant at Eastern EU firms, whereas *partOFlarge* and *rd* are insignificant in other EECA firms.

Regardless of the group of countries, model specification, or estimation method, human capital measured by employee skills contribute to this phenomenon positively, but its impact is not very big. On average, productivity is about 0.5% higher at firms that employ highly skilled workers than at those that do not. Human capital expressed by firm managers' experience is still insignificant in both groups of countries as observed in the joint model.

In addition to discrepancies in labour productivity distribution in the EU and non-EU groups of countries, we also observe significant differences in labour productivity when manufacturing and services are considered. Again, columns (1)–(9) in Tables 4 and 5, for manufacturing and services respectively, are analogous to those in Table 1, omitting *sector*.

Taking into account firm age, the difference in coefficients and their significance is noticeable, however, the parabolic pattern remains. The model for productivity in manufacturing, unlike in services, is the first model in which firm age and its significance are not that clear. When we take a closer look at the coefficients, they suggest that service firms achieve higher levels of productivity than manufacturing firms, and that growth is more rapid, a pattern that is similar to the one seen in EU countries. The decline in productivity based on the non-linear character of the relationship is also less pronounced in services. Comparing productivity factors more globally, we see that their importance in supporting productivity is much more visible when service firms are analysed as a group. Firm size, being a part of a larger company, exporting status, both forms of innovation, the use of ICT, and worker skills boost productivity in services. Manufacturing firms show a strong impact on productivity when they engage in exporting, have a foreign owner or highly skilled workers, and when they engage in at least one of the four forms of innovation. Productivity is also supported by the use of foreign technology.

6 Conclusions

This paper investigates the determinants of labour productivity at Eastern European and Central Asian firms, paying special attention to the role of particular factors in manufacturing and services. Our analysis of a comprehensive sample of firms in the EBRD-WB BEEPS provides also additional insights on labour productivity differences between Eastern EU countries and the EECA countries.

The micro-econometric analysis underscores firm heterogeneity in labour productivity growth. Firm characteristics play a large role. Young, large exporters with foreign ownership enjoy higher productivity. Our results are in line with the existing empirical literature on firm-export performance, i.e. that exporters are more productive that non-exporters (see Melitz 2003; Bernard et al. 2012; Melitz, Redding 2014; Helpman 2018 – for recent review of the literature). Additionally, Brakman et al. (2019) point out that other firm characteristics, especially firm size (i.e. being a large firm) and foreign ownership are important determinants of a firm's productivity and therefore its future export activity. Our analysis strongly supports this thesis.

We also find that among Eastern European and Central Asian firms highly skilled workers supported by ICT use and intensive innovation activities foster labour productivity growth. Our results are entirely consistent with the findings of Rukumnuaykit and Pholphirul (2016), Bank of Malta (2018), Sasso and Ritzen (2019) and Okumu and Mawejje (2019), who underline a positive impact of a skilled workforce on labour productivity. This determinant of labour productivity is especially important, because nowadays many organisations continue to deal with skills shortage and evidence from the European Union, the US and Japan in the last five years shows that highly skilled workers remain in ever greater demand relative to medium- and low-skilled workers (Hays 2017). Genuine skill constraints can negatively affect labour productivity in the future and hamper the ability to innovate and adopt technological developments (Brunello, Wruuck 2019). Our findings also support diffusion and research effects observed by Cörvers (1997). The effects show how better-educated workers supported by ICT use and participation in R&D activities could influence labour productivity growth.

The analysis shows that specific determinants play different roles depending on the sector in a firm is operating and where it is located. Enterprises in countries that are EU members and are foreign owned on average have higher productivity then firms in countries that are not EU members. These conclusions are in line with the results of previous analyses showing that the joining to the regional grouping changes the way, in which participating economies achieve growth and contributes to increased productivity (Lee et al. 2013; Campos, Coricelli, Moretti 2014). This positive effect of membership in regional grouping on labour productivity is mainly transmitted by the trade channel – greater availability of world class inputs, technology acquisition via import or exports, import discipline, higher turnover and by the foreign direct investment channel – through the entry effect, competition, knowledge spillovers and linkage effects (López-Córdova, Moreira 2003).

Our findings lead to some important implications for policies on labour productivity growth in Eastern European and Central Asian firms. Of course, there is no 'one-size-fits-all' policy that can be implemented in EECA countries, but we can offer some general recommendations. We show that the more productive a company, the more important the innovative sources of productivity. We recommend that government support programmes be put in place in highly productive companies, which often require a higher level of ICT complementarity to boost productivity. Our findings also suggest that favourable business conditions need to be created for the most productive firms, facilitating technology diffusion. Incentives should focus on ICT activity, which will create strong potential for spillovers, including linkages between foreign and local firms, education, training, and R&D. In the paper, we underline the importance of investment in human capital (higher skills), providing recommendations for the government to design financial incentives and favourable tax policies that encourage individuals and employers to invest in tertiary education and on-the-job training for all workers.

Our study has some limitations. First, causality issues may result from any unobservable not identified variables in the matching model and may also arise from the cross-sectional nature of the data. Second, the limited availability of data forced us to use total sales per employee as our main dependent variable.

Further research utilising the BEEPS data should try to incorporate the evolution of firms and their adaptation to changing economic conditions (use of lagged variables). However, this requires a panel dataset. It would also be fruitful to match micro-survey information in the BEEPS with other databases, such as firms' balance sheets. In this regard, an interesting avenue for future research will be to focus on a better understanding of the relationship between productivity, investment, and financing conditions.

We also recommend in the future to carry out an in-depth study on the impact of ICT and innovation on labour productivity, as soon as data at the micro level are available. The increased interest in the "productivity paradox" (Brynjolfsson 1993) and its possible explanations (Brynjolfsson, Rock, Syverson 2017) indicate that to better understand ICT impact on labour productivity growth it is necessary to update the economic measurement of ICTs. It is especially important to split ICTs assets into tangible ICT assets (hardware for information and communication technologies) and intangible ICT assets (software and databases), as well as R&D. Nowadays, successful companies do not need large investments in factories or even computer hardware, but they do have intangible assets that are costly to replicate. Most recent studies based on macro data highlight the importance of economic policies facilitating the accumulation of intangible assets (also ICT assets) as integral elements of productivity growth (Adarov, Stehrer 2019). So, it is important to check the role of tangible and intangible ICT based on micro data.

References

Adarov A., Stehrer R. (2019), Tangible and intangible assets in the growth performance of the EU, Japan and the US, *Wiener Institut für Internationale Wirtschaftsvergleiche Research Report*, 442, October, 1–56.

Aiello F., Ricotta F. (2016), Firm heterogeneity in productivity across Europe: evidence from multilevel models, *Economics of Innovation and New Technology*, 25(1), 57–89.

Alvarez R., Lopez R. (2005), Exporting and performance: evidence from Chilean plants, *Canadian Journal of Economics*, 38, 1384–1400.

Arrow K. (1962), The economic implications of learning by doing, *Review of Economic Studies*, 29(3), 155–173.

Ayodele A., Ahmed A., Loffredo M., Sebastiano C. (2017), *The role of ICT in labor productivity*, https://www.researchgate.net/publication/329248125_The_Role_of_ICT_in_Labor_Productivity/stats/.

Balci B., Hollmann A., Rosenkranz C. (2011), *Service productivity: a literature review and research agenda*, XXI International RESER Conference, http://www.reser.net/materiali/priloge/slo/balci_et_at.pdf.

Bank of Malta (2018), Determinants of labour productivity in Malta from a firm-level survey, *Quarterly Review*, 3, 43–49.

Barron D.N., West E., Hannan M.T. (1994), A time to growth and a time to die: growth and mortality of credit unions in New York, 1914–1990, *American Journal of Sociology,* 100(2), 381–421.

Bartel A.P., Ichniowski C., Shaw K. (2007), How does information technology really affect productivity? Plant-level comparisons of product innovation, process improvement and worker skills, *Quarterly Journal of Economics*, 122(4), 1721–1758.

Bartelsman E., Doms M. (2000), Understanding productivity: lessons from longitudinal microdata, *Journal of Economic Literature*, 38(3), 569–594.

Bartelsman E., Haltiwanger J., Scarpetta S. (2013), Cross-country differences in productivity: the role of allocation and selection, *American Economic Review*, 103(1), 305–334.

Baum C., Schaffer M. (2012), *ivreg2h: Stata module to perform instrumental variables estimation using heteroskedasticity-based instruments*, http://ideas.repec.org/c/boc/bocode/ s457555.html.

Baumann J., Kritikos A. (2017), *The link between R&D, innovation and productivity: Are micro firms different?,* Forschungsinstitut zur Zukunft der Arbeit Institute for the Study of Labor Discussion Paper, 9734.

Benkovskis K., Masso J., Tkacevs O., Vahter P., Yashiro N. (2017), *Export and productivity in global value chains: comparative evidence from Latvia and Estonia*, OECD Economics Department Working Paper, 14448.

Berlingieri G., Calligaris S., Criscuolo C. (2018), The productivity-wage premium: Does size still matter in a service economy? *AEA Papers and Proceedings*, 108, 328–333.

Bernard A., Jensen B., Redding S.J., Schott P. (2012), The empirics of firm heterogeneity and international trade, *Annual Review of Economics*, 4, 283–313.

Bernard A., Dhyne E., Magerman G., Manova K., Moxnes A. (2019), *The origins of firm heterogeneity: a production network approach*, NBER Working Paper, 25441.

Blonigen B., Fontagné L., Sly N., Toubal F. (2012), *Cherries for sale: export networks and the incidence of cross-border M&A*, NBER Working Paper, 18414, March.

Bloom N., Genakos C., Sadun R., Van Reene J. (2012), Management practices across firms and countries, *Academy of Management Perspectives*, 26(1), 32–67.

Botrić V., Božić L., Broz T. (2017), Explaining firm-level total factor productivity in post-transition: manufacturing vs. services sector, *Journal of International Studies*, 10(3), 77–90.

Brakman S., Garretsen H., van Maarseveen R., Zwaneveld P. (2019), Firm heterogeneity and exports in the Netherlands: identifying export potential beyond firm productivity, *The Journal of International Trade and Economic Development*, DOI:10.1080/09638199.2019.1631876.

Brunello G., Wruuck P. (2019), *Skill shortages and skill mismatch in Europe: a review of the literature*, IZA Working Papers, 12346.

Brynjolfsson E. (1993), The productivity paradox of information technology, *Communications of the ACM*, 36(12), 67–77.

Brynjolfsson E., Rock D., Syverson C. (2017), *Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics,* NBER Technical Working Papers, 24001.

Campos N., Coricelli F., Moretti L. (2014), *Economic growth and political integration: estimating the benefits from membership in the European Union*, CEPR Discussion Paper, 9968.

Cardona M., Kretschmer T., Strobel T. (2013), ICT and productivity: conclusions from the empirical literature, *Information Economics and Policy*, 25(3), 109–125.

Cieślik A., Gauger I., Michałek J. (2017), Determinants of productivity of Ukrainian firms, *Comparative Economic Research*, 20(1), 1–15.

Coad A., Segarra A., Teruel M. (2013), Like milk or wine: Does firm performance improve with age?, *Structural Change and Economic Dynamics*, 24, 173–189.

CompNet Task Force (2014), *Micro-based evidence of EU competitiveness: the CompNet database*, European Central Bank Working Paper, 1634.

Cörvers F. (1997), The impact of human capital on labour productivity in manufacturing sectors of the European Union, *Applied Economics*, 29(8), 975–987.

De Loecker J. (2007), Do exports generate higher productivity? Evidence from Slovenia, *Journal of International Economics*, 73(1), 69–98.

De Loecker J. (2013), Detecting learning by exporting, *American Economic Journal: Microeconomics*, 5(3), 1–21.

Dobmeier M. (2016), Understanding and managing service productivity: a literature review, *Journal of Business Market Management*, 9(1), 518–540.

Dosi G., Lechevalier S., Secchi A. (2010), Introduction: interfirm heterogeneity: nature, sources and consequences for industrial dynamics, *Industrial and Corporate Change*, 19(6), 1867–1890.

Driffield N., Sun K., Temouri Y. (2018), Investigating the link between foreign ownership and firm performance: an endogenous threshold approach, *Multinational Business Review*, 26(3), 277–298.

Du J., Temouri Y. (2015), High-growth firms and productivity: evidence from the United Kingdom, *Small Business Economics*, 44(1), 123–143.

Ekiert G. (2015), Three generations of research on post communist politics: a sketch, *East European Politics and Societies and Cultures*, 29(2), 323–337.

Feenstra R., Kee H.L. (2008), Export variety and country productivity: estimating the monopolistic competition model with endogenous productivity, *Journal of International Economics*, 74(2), 500–518.

EBRD (2017), *Transition Report 2017–2018*, European Bank for Reconstruction and Development, https://www.ebrd.com/transition-report-2017-18/.

Foster L., Grim C., Haltiwanger J., Wolf Z. (2018), *Innovation, productivity dispersion, and productivity growth*, NBER Working Paper, 24420.

Fotros M., Ahmadvand N. (2017), Impact of import and export of high technology industries on economic growth of Iran, *Quarterly Journal of Quantitative Economics*, 14(2), 1–24.

Greenaway D., Guariglia A., Yu Z. (2014), The more the better? Foreign ownership and corporate performance in China, *European Journal of Finance*, 20, 681–702.

Guadalupe M., Kuzmina O., Thomas C. (2012), Innovation and foreign ownership, *American Economic Review*, 102(7), 3594–3627.

Haldane A. (2017), *The UK's productivity problem: Hub no spokes*, Bank of England, https://www.bankofengland.co.uk/-/media/boe/files/speech/2018/the-uks-productivity-problem-hub-no-spokes-speech-by-andy-haldane/.

Hall B. (2011), *Innovation and productivity*, NBER Technical Working Papers, 17178.

Hannan M.T., Freeman J. (1984), Structural inertia and organizational change, *American Sociological Review*, 49, 149–164.

Hays (2017), *Regional dynamics of the global labour markets skills demand and tomorrow's workforce: the Hays Global Skills Index 2017*, https://www.hays-index.com/wp-content/uploads/2017/09/Hays-GSI-2017-Report.pdf.

Hecht J. (2018), Research and development and labour productivity: Do high-tech firms exhibit labour- or capital-saving technical change?, *Applied Economics*, 50(16), 1790–1811.

Helpman E. (2018), *Globalization and Inequality*, Harvard University Press.

Hosono K., Miyakawa D., Takizawa M. (2015), *Learning by export: Does the presence of foreign affiliate companies matter?,* RIETI Discussion Paper, 15-E-053.

IMF (2018), *Czech Republic: selected issues*, IMF Country Report, 18/188, International Monetary Fund.

Javorcik B. (2004), Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages, *American Economic Review*, 94(3), 605–627.

Jovanovic B. (1982), Selection and the evolution of industry, *Econometrica*, 50, 649–670.

Koch M., Smolka M. (2017), *Foreign ownership and skill-biased technological change*, https://www.econstor.eu/bitstream/10419/168202/1/VfS-2017-pid-3149.pdf.

Lagesse G. (2018), An analysis of the effects of aging and experience on firms' performance, in: A. Heshmati, H. Yoon (eds), *Economic Growth and Development in Ethiopia. Perspectives on Development in the Middle East and North Africa (MENA) Region*, Springer.

Lauzadyte-Tutliene A., Balezentis T., Goculenko E. (2018), Welfare state in Central and Eastern Europe, *Economics and Sociology*, 11(1), 100–123.

Lee J.Y., Kim D. (2013), *Different models for regional integration: lessons from total factor productivity in Europe*, ADBI Working Paper, 452.

Leung D., Césaire M., Terajima Y. (2008), *Firm size and productivity*, Bank of Canada Working Papers, 45.

Levenko N., Oja K., Staehr K. (2019), Total factor productivity growth in Central and Eastern Europe before, during and after the global financial crisis, *Post-Communist Economies*, 31(2), 137–160.

Lewbel A. (2012), Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models, *Journal of Business and Economic Statistics*, 30(1), 67–80.

López-Córdova E., Moreira M.M. (2003), Regional integration and productivity: the experiences of Brazil and Mexico, *BID-INTAL*, 14, 1–60.

Lucas R.E. (1988), On the mechanics of economic development, *Journal of Monetary Economics*, 22, 3–42.

Manjon M., Manez L., Rochina-Barrachina M., Sanchis-Llopis J. (2013), Reconsidering learning by exporting, *Review of World Economy*, 149, 5–22.

Masso J., Vahter P. (2015), Exporting and productivity: the effects of multi-product and multi-market export entry, *Scottish Journal of Political Economy*, 62(4), 325–350.

Melitz M. (2003), The impact of trade on intra-industry reallocations and aggregate industry productivity, *Econometrica*, 71(6), 1695–1725.

Melitz M., Redding S.J. (2014), Heterogeneous firms and trade, in: G. Gopinath, E. Helpman, K. Rogoff (eds), *Handbook of International Economics*, Elsevier.

Moral-Benito E. (2016), *Growing by learning: firm-level evidence on the size-productivity nexus*, Banco de España Working Paper, 1613.

Nguyen H., Nishijima S. (2009), *Export intensity and impacts from firm characteristics, domestic competition and domestic constraints in Vietnam: a micro-data analysis*, Kobe University Research Institute for Economics & Business Administration Discussion Paper Series, 238.

Nurmilaakso J. (2009), ICT solutions and labor productivity: evidence from firm-level data, *Electronic Commerce Research*, 9, 173–181.

OECD (2009), *OECD Science, Technology and Industry Scoreboard 2009*, https://doi.org/10.1787/sti_scoreboard-2009-en/.

OECD (2016), *Economic Policy Reforms 2016 Going for Growth Interim Report*, https://www.ebrd.com/transition-report-2017-18/.

OECD (2018), *Multi-Dimensional Review of Thailand: Volume 1, Initial Assessment*.

Okumu I., Mawejje J. (2019), Skills and labour productivity in African manufacturing, *Development Policy Review*, https://doi.org/10.1111/dpr.12431.

Oulton N. (2012), Long-term implications of the ICT revolution: applying the lessons of growth theory and growth accounting, *Economic Modelling*, 29(5), 1722–1736.

Palangkaraya A., Yong J., Stierwald A. (2009), Is firm productivity related to size and age? The case of large Australian firms, *Journal of Industry, Competition and Trade*, 9(2), 167–195.

Papa J., Rehill L., O'Connor B. (2018), *Patterns of firm-level productivity in Ireland*, OECD Working Paper, 15, March.

Pervan M., Pervan I., Ćurak M. (2017), The influence of age on firm performance: evidence from the Croatian food industry, *Journal of Eastern Europe Research in Business and Economics*, 618681, 1–9.

Peters B. (2005), *The relationship between product and process innovations and firm performance: microeconometric evidence*, Centre for European Economic Research (ZEW), https://pdfs.semanticscholar.org/01a4/534a7cb4cdc4d37cc7bfeec7c9c5b9c60218.pdf.

Relich M. (2017), The impact of ICT on labor productivity in the EU, *Information Technology for Development*, 23(4), 706–722.

Romer P.M. (1986), Increasing returns and long-run growth, *Journal of Political Economy*, 94, 1002–1037.
Rukumnuaykit P., Pholphirul P. (2016), Human capital linkages to labour productivity: implications from Thai manufacturers, *Journal of Education and Work*, 29(8), 922–955.
Sangho K. (2018), Firm heterogeneity in sources of total factor productivity growth for Japanese manufacturing firms, *Applied Economics*, 50(58), 1–15.
Sasso S., Ritzen J. (2019), Sectoral cognitive skills, R&D, and productivity: a cross-country cross-sector analysis, *Education Economics*, 27(1), 35–51.
Schwarzer J. (2017), *The effects of exporting on labour productivity: evidence from German firms*, Council on Economic Policies Working Paper, 1702.
Silva A., Afonso O., Africano A. (2012), Learning-by-exporting: What we know and what we would like to know, *International Trade Journal*, 26, 255–288.
Srinivasan T.N., Archana V. (2011), Determinants of export decision of firms, *Economic and Political Weekly*, 46(7), 49–58.
Syverson C. (2004), Product substitutability and productivity dispersion, *Review of Economics and Statistics*, 86(2), 534–550.
Syverson C. (2011), What determines productivity?, *Journal of Economic Literature*, 49(2), 326–365.
Temouri Y., Vogel A., Wagner J. (2013), Self-selection into export markets by business services firms: evidence from France, Germany and the United Kingdom, *Structural Change and Economic Dynamics*, 25, 146–158.
Vassilakis S. (2008), Learning-by-doing, in: S. Durlaf, L.E. Blume (eds), *The New Palgrave Dictionary of Economics*, Palgrave Macmillan.
Vuegelers R. (2011), Assessing the potential for knowledge-based development in the transition countries of Central and Eastern Europe, the Caucasus and Central Asia, *Society and Economy*, 33(3), 475–501.
Waldkirch A. (2014), *Foreign firms and productivity in developing countries*, https://www.uml.edu/docs/Waldkirch_Forfirmsprod_tcm18-147190.pdf.
Weche-Gelübcke J. (2013), Foreign and domestic takeovers in Germany: cherry-picking and lemon--grabbing, *Applied Economics Quarterly*, 59(4), 275–294.
Wignaraja G. (2012), Innovation, learning and exporting in China: Does RD or a technology index matter?, *Journal of Asian Economics*, 23(3), 224–233.
Wignaraja G. (2015), Factors affecting entry into supply chain trade: an analysis of firms in Southeast Asia, *Asia & the Pacific Policy Studies*, 2(3), 623–642.

Acknowledegments

The authors gratefully acknowledge participants of the conference "Produktywność gospodarki: uwarunkowania, determinanty, perspektywy" in Wrocław for their comments on an earlier draft of this paper, as well as two anonymous referees for their careful reading and useful remarks.

Appendix

Table 1
Determinants of labour productivity in Eastern European and Central Asian countries

	OLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
ln_*age*	0.324***	0.360***	0.362***	0.376***	0.378***	0.344***	0.344***	0.318***	0.319***
	[0.108]	[0.108]	[0.105]	[0.106]	[0.103]	[0.105]	[0.103]	[0.102]	[0.099]
ln_*age2*	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***	-0.08***
	[0.020]	[0.020]	[0.019]	[0.020]	[0.019]	[0.020]	[0.019]	[0.018]	[0.017]
size	0.147**	0.140*	0.136*	0.148**	0.144**	0.131*	0.131*	0.132*	0.130*
	[0.070]	[0.070]	[0.071]	[0.070]	[0.071]	[0.070]	[0.071]	[0.070]	[0.071]
partOFlarge	0.140	0.112	0.109	0.108	0.104	0.109	0.108	0.118	0.115
	[0.088]	[0.088]	[0.091]	[0.088]	[0.091]	[0.091]	[0.093]	[0.086]	[0.088]
fowner	0.359***	0.317***	0.311***	0.303***	0.296***	0.327***	0.324***	0.329***	0.324***
	[0.061]	[0.064]	[0.071]	[0.064]	[0.071]	[0.062]	[0.069]	[0.067]	[0.074]
export	0.159***	0.112***	0.156**	0.128***	0.180**	0.110**	0.119*	0.136***	0.172**
	[0.043]	[0.040]	[0.070]	[0.035]	[0.072]	[0.042]	[0.062]	[0.037]	[0.077]
inno		0.047***	0.046***			0.045***	0.045***	0.056***	0.054***
		[0.009]	[0.010]			[0.010]	[0.011]	[0.009]	[0.009]
rd				0.090	0.084				
				[0.059]	[0.065]				
Ftech		0.133***	0.129***	0.150***	0.146***			0.153***	0.150***
		[0.031]	[0.030]	[0.031]	[0.031]			[0.030]	[0.030]
ICT						0.223***	0.222***		
						[0.068]	[0.068]		
workerskill		0.005***	0.005***	0.005***	0.005***	0.005***	0.005***		
		[0.001]	[0.000]	[0.001]	[0.000]	[0.001]	[0.001]		
managerskill								0.000	0.000
								[0.001]	[0.001]
EU		1.436***	2.122***	1.439***	2.127***	1.204***	2.108***	1.423***	2.043***
		[0.024]	[0.030]	[0.024]	[0.029]	[0.032]	[0.023]	[0.020]	[0.033]
sector		0.425***	0.451***	0.452***	0.459***	0.471***	0.480***	0.434***	0.206**
		[0.085]	[0.094]	[0.107]	[0.095]	[0.085]	[0.094]	[0.081]	[0.098]
_cons	9.074***	8.487***	10.33***	8.437***	10.32***	8.325***	10.34***	8.619***	10.32***
	[0.118]	[0.175]	[0.016]	[0.192]	[0.017]	[0.189]	[0.014]	[0.155]	[0.018]
R2/R2c	0.267	0.279	0.279	0.281	0.281	0.281	0.281	0.273	0.273
N	12 362	11 716	11 716	11 774	11 774	11 778	11 778	11 905	11 905
idp			0.000		0.000		0.000		0.000

Notes:
* p < 0.10, ** p < 0.05, *** p < 0.01, clustered robust errors by country in square brackets. All specifications include individual effects for both industries and countries. The figures reported for the *idp* are the p-values and refer to the Kleibergen-Paap rk LM test statistic.

Table 2
Determinants of labour productivity for Eastern EU countries

	OLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln_*age*	0.555** [0.212]	0.543** [0.206]	0.545*** [0.195]	0.551** [0.211]	0.553*** [0.199]	0.514** [0.218]	0.516** [0.206]	0.520** [0.189]	0.520*** [0.180]
ln_*age2*	-0.103** [0.040]	-0.101** [0.039]	-0.10*** [0.037]	-0.102** [0.040]	-0.10*** [0.037]	-0.094** [0.041]	-0.094** [0.038]	-0.097** [0.035]	-0.10*** [0.034]
size	0.052 [0.064]	0.068 [0.059]	0.065 [0.052]	0.068 [0.059]	0.06 [0.052]	0.055 [0.059]	0.052 [0.052]	0.049 [0.055]	0.049 [0.049]
partOFlarge	0.236* [0.119]	0.203 [0.119]	0.200* [0.114]	0.178 [0.122]	0.172 [0.117]	0.222* [0.118]	0.219* [0.114]	0.258* [0.121]	0.258** [0.115]
fowner	0.487*** [0.087]	0.445*** [0.082]	0.439*** [0.083]	0.428*** [0.084]	0.416*** [0.083]	0.447*** [0.083]	0.442*** [0.084]	0.467*** [0.084]	0.466*** [0.084]
export	0.184*** [0.049]	0.131*** [0.035]	0.170* [0.083]	0.141*** [0.045]	0.234*** [0.068]	0.125*** [0.033]	0.159* [0.091]	0.168*** [0.042]	0.174* [0.105]
inno		0.011 [0.014]	0.009 [0.015]			0.008 [0.013]	0.006 [0.014]	0.023 [0.015]	0.023 [0.017]
rd				0.103 [0.090]	0.089 [0.084]				0.097 [0.064]
Ftech		0.046 [0.069]	0.043 [0.064]	0.049 [0.065]	0.043 [0.061]			0.097 [0.068]	
ICT						0.327*** [0.084]	0.326*** [0.080]		
workerskill		0.006*** [0.001]	0.006*** [0.001]	0.006*** [0.001]	0.006*** [0.001]	0.006*** [0.001]	0.006*** [0.001]		
managerskill								0.002 [0.002]	0.002 [0.002]
sector		0.159 [0.122]	0.578*** [0.157]	0.155 [0.122]	0.609*** [0.152]	0.455*** [0.083]	0.588*** [0.176]	0.15 [0.126]	0.338** [0.136]
_cons	10.26*** [0.323]	10.05*** [0.288]	11.70*** [0.048]	10.06*** [0.295]	11.66*** [0.050]	9.563*** [0.379]	11.67*** [0.083]	10.10*** [0.253]	11.56*** [0.049]
R2/R2c	0.213	0.228	0.228	0.227	0.227	0.232	0.232	0.219	0.219
N	3353	3161	3161	3184	3184	3176	3176	3222	3222
idp			0.000		0.000		0.000		0.000

Notes:
*p < 0.10, **p < 0.05, ***p < 0.01, clustered robust errors by country in square brackets. All specifications include individual effects for both industries and countries. The figures reported for the *idp* are the p-values and refer to the Kleibergen-Paap rk LM test statistic.

Table 3

Determinants of labour productivity for Eastern non-EU countries and Central Asian countries

	OLS	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
ln_*age*	0.251* [0.128]	0.306** [0.131]	0.308** [0.124]	0.325** [0.126]	0.327*** [0.120]	0.290** [0.127]	0.291** [0.102]	0.267** [0.124]	0.269** [0.118]
ln_*age2*	-0.067** [0.024]	-0.07*** [0.025]	-0.07*** [0.024]	-0.08*** [0.024]	-0.08*** [0.023]	-0.07*** [0.024]	-0.07*** [0.023]	-0.07*** [0.023]	-0.07*** [0.021]
size	0.182* [0.090]	0.166* [0.092]	0.161* [0.095]	0.179* [0.091]	0.174* [0.092]	0.160* [0.091]	0.157* [0.093]	0.164* [0.091]	0.160* [0.094]
partOFlarge	0.11 [0.109]	0.082 [0.108]	0.077 [0.111]	0.087 [0.109]	0.083 [0.111]	0.072 [0.108]	0.07 [0.108]	0.073 [0.102]	0.07 [0.105]
fowner	0.257** [0.105]	0.215* [0.108]	0.207* [0.118]	0.205* [0.107]	0.198* [0.116]	0.224** [0.105]	0.219* [0.114]	0.220* [0.111]	0.213* [0.121]
export	0.143** [0.058]	0.097* [0.055]	0.164* [0.091]	0.114** [0.047]	0.171* [0.098]	0.097 [0.060]	0.134* [0.075]	0.118** [0.049]	0.178* [0.107]
inno		0.062*** [0.008]	0.060*** [0.009]			0.060*** [0.008]	0.059*** [0.009]	0.069*** [0.008]	0.068*** [0.009]
rd				0.083 [0.075]	0.076 [0.083]				
Ftech		0.171*** [0.028]	0.165*** [0.027]	0.195*** [0.027]	0.189*** [0.028]			0.181*** [0.029]	0.175*** [0.032]
ICT						0.201** [0.078]	0.201*** [0.077]		
workerskill		0.005*** [0.001]	0.005*** [0.001]	0.005*** [0.001]	0.005*** [0.001]	0.005*** [0.001]	0.005*** [0.001]		
managerskill								-0.001 [0.001]	-0.001 [0.001]
sector	M	0.409*** [0.112]	0.407*** [0.108]	0.403*** [0.113]	0.402*** [0.109]	0.229 [0.155]	0.435*** [0.109]	0.166 [0.123]	0.165 [0.119]
_cons	9.143*** [0.142]	8.557*** [0.178]	10.01*** [0.020]	8.532*** [0.170]	10.00*** [0.021]	8.645*** [0.232]	10.02*** [0.018]	8.928*** [0.178]	10.00*** [0.022]
R2/R2c	0.217	0.231	0.231	0.233	0.233	0.232	0.232	0.225	0.225
N	9009	8555	8555	8590	8590	8602	8602	8683	8683
idp			0.000		0.000		0.000		0.000

Notes:
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, clustered robust errors by country in square brackets. All specifications include individual effects for both industries and countries. The figures reported for the *idp* are the p-values and refer to the Kleibergen-Paap rk LM test statistic.

Table 4

Determinants of labour productivity in manufacturing in EECA countries

	OLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln_*age*	0.187 [0.165]	0.232 [0.168]	0.232 [0.162]	0.228 [0.169]	0.23 [0.162]	0.214 [0.165]	0.212 [0.160]	0.213 [0.154]	0.211 [0.149]
ln_*age2*	-0.049 [0.029]	-0.056* [0.030]	-0.056* [0.029]	-0.055* [0.031]	-0.055* [0.029]	-0.052* [0.030]	-0.052* [0.029]	-0.053* [0.027]	-0.053** [0.026]
size	0.101** [0.047]	0.079* [0.046]	0.080 [0.059]	0.088* [0.046]	0.081* [0.049]	0.079* [0.042]	0.084 [0.056]	0.072 [0.045]	0.078 [0.056]
partOFlarge	0.049 [0.154]	0.013 [0.141]	0.014 [0.146]	0.014 [0.139]	0.01 [0.143]	0.018 [0.136]	0.021 [0.142]	0.023 [0.136]	0.026 [0.142]
fowner	0.328*** [0.085]	0.265*** [0.089]	0.266*** [0.101]	0.259*** [0.089]	0.252*** [0.096]	0.293*** [0.088]	0.299*** [0.102]	0.291*** [0.092]	0.297*** [0.105]
export	0.195*** [0.038]	0.166*** [0.033]	0.160 [0.115]	0.182*** [0.032]	0.228* [0.135]	0.161*** [0.037]	0.126 [0.149]	0.170*** [0.034]	0.126 [0.178]
inno		0.057*** [0.015]	0.057*** [0.016]			0.056*** [0.016]	0.057*** [0.019]	0.067*** [0.013]	0.069*** [0.015]
rd				0.029 [0.099]	0.024 [0.104]				
Ftech		0.228*** [0.055]	0.228*** [0.056]	0.248*** [0.055]	0.244*** [0.053]			0.222*** [0.050]	0.225*** [0.054]
ICT						0.189** [0.072]	0.191** [0.076]		
workerskill		0.004*** [0.001]	0.004*** [0.001]	0.004*** [0.001]	v0.004*** [0.001]	0.004*** [0.001]	v0.004*** [0.001]		
managerskill								-0.002 [0.001]	-0.002 [0.002]
EU		1.567*** [0.039]	1.812*** [0.072]	1.425*** [0.021]	1.819*** [0.056]	1.438*** [0.017]	1.764*** [0.061]	1.564*** [0.041]	1.833*** [0.093]
_*cons*	9.386*** [0.201]	9.258*** [0.205]	10.18*** [0.053]	9.262*** [0.203]	10.18*** [0.048]	9.199*** [0.225]	10.20*** [0.055]	9.326*** [0.193]	10.15*** [0.068]
R2/R2c	0.257	0.273	0.273	0.272	0.272	0.272	0.272	0.269	0.269
N	5127	4826	4826	4858	4858	4856	4856	4921	4921
idp			0.000		0.000		0.000		0.000

Notes:
*p < 0.10, **p < 0.05, ***p < 0.01; clustered robust errors by country in square brackets. All specifications include both individual effects for industries and for countries. The figures reported for the *idp* are the p-values and refer to the Kleibergen-Paap rk LM test statistic.

Table 5

Determinants of labour productivity for service industries in EECA countries

	OLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln_*age*	0.427***	0.446***	0.446***	0.469***	0.469***	0.424***	0.425***	0.403***	0.402***
	[0.116]	[0.109]	[0.107]	[0.108]	[0.105]	[0.107]	[0.105]	[0.111]	[0.109]
ln_*age2*	-0.10***	-0.09***	-0.09***	-0.10***	-0.10***	-0.10***	-0.10***	-0.09***	-0.09***
	[0.025]	[0.023]	[0.022]	[0.022]	[0.022]	[0.023]	[0.022]	[0.023]	[0.023]
size	0.185**	0.187**	0.186**	0.197**	0.197**	0.174*	0.174*	0.181*	0.180**
	[0.090]	[0.090]	[0.089]	[0.090]	[0.088]	[0.092]	[0.091]	[0.091]	[0.090]
partOFlarge	0.209**	0.182*	0.180**	0.177*	0.176**	0.176*	0.177*	0.188**	0.186**
	[0.086]	[0.091]	[0.087]	[0.088]	[0.085]	[0.098]	[0.094]	[0.091]	[0.088]
fowner	0.396***	0.368***	0.364***	0.348***	0.345***	0.364***	0.367***	0.374***	0.371***
	[0.089]	[0.092]	[0.092]	[0.092]	[0.092]	[0.093]	[0.091]	[0.088]	[0.087]
export	0.154*	0.093	0.125*	0.114	0.140**	0.096	0.075	0.137*	0.160**
	[0.079]	[0.081]	[0.076]	[0.071]	[0.071]	[0.079]	[0.087]	[0.077]	[0.074]
inno		0.042***	0.041***			0.037***	0.038***	0.048***	0.047***
		[0.012]	[0.012]			[0.012]	[0.012]	[0.011]	[0.012]
rd				0.175**	0.172***				
				[0.068]	[0.065]				
Ftech		0.033	0.031	0.05	0.048			0.081	0.079
		[0.051]	[0.049]	[0.047]	[0.047]			[0.053]	[0.052]
ICT						0.241***	0.241***		
						[0.075]	[0.074]		
workerskill		0.006***	0.006***	0.006***	0.006***	0.006***	0.006***		
		[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]		
managerskill								0.002	0.002
								[0.002]	[0.002]
EU		1.482***	2.281***	1.487***	2.274***	1.510***	2.282***	1.399***	2.142***
		[0.041]	[0.038]	[0.039]	[0.044]	[0.033]	[0.046]	[0.037]	[0.038]
_*cons*	8.527***	8.641***	10.17***	8.221***	10.17***	8.453***	10.17***	8.859***	10.25***
	[0.168]	[0.131]	[0.030]	[0.183]	[0.031]	[0.136]	[0.029]	[0.127]	[0.037]
R2/R2c	0.265	0.277	0.277	0.28	0.28	0.28	0.28	0.268	0.268
N	7235	6890	6890	6916	6916	6922	6922	6984	6984
idp			0.000		0.000		0.000		0.000

Notes:

*p < 0.10, **p < 0.05, ***p < 0.01; clustered robust errors by country in square brackets. All specifications include both individual effects for industries and for countries. The figures reported for the *idp* are the p-values and refer to the Kleibergen-Paap rk LM test statistic.

Table 6
Structure of database by country and by industry

Eastern EU countries			**Eastern non-EU and Asian countries**			**Manufacturing sector**			**Service sector**		
country	**N**	**%**	**country**	**N**	**%**	**NACE 1.1**	**N**	**%**	**NACE 1.1**	**N**	**%**
Bulgaria	293	1.77	Albania	360	2.17	15	1169	7.11	45	1343	8.17
Croatia	360	2.17	Armenia	360	2.17	16	29	0.18	50	442	2.69
Cyprus	360	2.17	Azerbaijan	390	2.36	17	330	2.01	51	2532	15.41
Czech Rep.	254	1.53	Belarus	360	2.17	18	581	3.53	52	3784	23.02
Estonia	273	1.65	Bosnia-Herzegovina	360	2.17	19	91	0.55	55	653	3.97
Greece	315	1.9	Macedonia	360	2.17	20	340	2.07	60	332	2.02
Hungary	310	1.87	Georgia	360	2.17	21	70	0.43	61	1	0.01
Latvia	336	2.03	Kazakhstan	600	3.62	22	379	2.31	62	1	0.01
Lithuania	270	1.63	Kosovo	200	1.21	23	14	0.09	63	290	1.76
Poland	542	3.27	Kyrgyzstan	270	1.63	24	404	2.46	64	164	1.00
Romania	540	3.26	Moldova	360	2.17	25	302	1.84	65	1	0.01
Slovakia	268	1.62	Mongolia	360	2.17	26	700	4.26	70	3	0.02
Slovenia	270	1.63	Montenegro	150	0.91	27	87	0.53	72	230	1.40
			Russia	4220	25.49	28	659	4.01			
			Serbia	360	2.17	29	548	3.33			
			Tajikistan	359	2.17	30	22	0.13			
			Turkey	1344	8.12	31	237	1.44			
			Ukraine	1002	6.05	32	30	0.18			
			Uzbekistan	390	2.36	33	183	1.11			
						34	44	0.27			
						35	58	0.35			
						36	346	2.11			
						37	37	0.23			

Source: author calculations based on BEEPS V.

Table 7
Descriptive statistics for total sample

Stats	N	Mean	Median	Sd	Skew-ness	Kurtosis	Min	Max
	Original data – total sample							
ln_*lpro*	12691	10.350	10.382	1.547	-0.370	8.492	-4.203	24.648
ln_*age*	16373	2.488	2.565	0.686	-0.274	3.753	0.000	5.165
size	16556	1.551	1.000	0.740	0.443	2.560	0.000	3.000
partOFlarge	16556	0.088	0.000	0.283	2.911	9.475	0.000	1.000
fowner	16387	0.050	0.000	0.219	4.113	17.916	0.000	1.000
export	16359	0.219	0.000	0.414	1.357	2.841	0.000	1.000
inno	16306	0.889	0.000	1.277	1.228	3.214	0.000	4.000
rd	16424	0.107	0.000	0.309	2.539	7.447	0.000	1.000
Ftech	16354	0.151	0.000	0.359	1.944	4.781	0.000	1.000
ICT	16484	0.819	1.000	0.385	-1.660	3.754	0.000	1.000
workerskill	15773	33.672	23.000	31.209	0.807	2.433	0.000	100.000
managerskill	16062	16.968	15.000	10.273	0.925	3.922	1.000	100.000
	Transformed data – total sample							
ln_*age*	16373	0.000	0.077	0.686	-0.274	3.753	-2.488	2.677
size	16556	0.000	-0.551	0.740	0.443	2.560	-1.551	1.449
partOFlarge	16556	0.000	-0.088	0.283	2.911	9.475	-0.088	0.912
fowner	16387	0.000	-0.050	0.219	4.113	17.916	-0.050	0.950
inno	16306	0.000	-0.889	1.277	1.228	3.214	-0.889	3.111
rd	16424	0.000	-0.107	0.309	2.539	7.447	-0.107	0.893
Ftech	16354	0.000	-0.151	0.359	1.944	4.781	-0.151	0.849
ICT	16484	0.000	0.181	0.385	-1.660	3.754	-0.819	0.181
workerskill	15773	0.000	-10.672	31.209	0.807	2.433	-33.672	66.328
managerskill	16062	0.000	-1.968	10.273	0.925	3.922	-15.968	83.032

Source: author calculations based on BEEPS V.

Table 8
Descriptive statistics for sub-samples

Stats	EU countries								Non-EU countries							
	N	mean	me-dian	sd	skew-ness	kurto-sis	min	max	N	mean	me-dian	sd	skew-ness	kurto-sis	min	max
ln_*lpro*	3514	11.035	11.061	1.445	0.357	8.613	3.259	24.648	9177	10.088	10.123	1.504	-0.669	9.012	-4.203	19.261
ln_*age*	4335	2.691	2.833	0.676	-0.732	5.106	0	5.088	12038	2.415	2.485	0.674	-0.136	3.591	0	5.165
size	4391	1.451	1	0.756	0.599	2.800	0	3	12165	1.588	1	0.731	0.398	2.499	0	3
partOFlarge	4391	0.073	0	0.260	3.286	11.800	0	1	12165	0.093	0	0.291	2.797	8.821	0	1
fowner	4323	0.087	0	0.283	2.921	9.532	0	1	12064	0.037	0	0.189	4.902	25.027	0	1
export	4314	0.321	0	0.467	0.768	1.589	0	1	12045	0.183	0	0.387	1.641	3.691	0	1
inno	4317	1.044	0	1.307	0.989	2.705	0	4	11989	0.833	0	1.261	1.327	3.462	0	4
rd	4361	0.128	0	0.334	2.225	5.948	0	1	12063	0.100	0	0.300	2.673	8.146	0	1
Ftech	4344	0.169	0	0.375	1.767	4.122	0	1	12010	0.145	0	0.352	2.015	5.060	0	1
ICT	4374	0.902	1	0.297	-2.703	8.305	0	1	12110	0.789	1	0.408	-1.420	3.016	0	1
workerskill	4160	20.983	10	25.577	1.626	5.018	0	100	11613	38.217	30	31.784	0.603	2.103	0	100
managerskill	4263	20.253	20	10.264	0.591	3.214	1	63	11799	15.781	14	10.016	1.101	4.516	1	100

Table 8, con't

Stats	Manufacturing								Services							
	N	mean	median	sd	skewness	kurtosis	min	max	N	mean	median	sd	skewness	kurtosis	min	max
ln_*lpro*	5313	10.142	10.185	1.524	-0.867	10.638	-4.20	18.180	7378	10.500	10.534	1.546	-0.046	6.970	-1.276	24.648
ln_*age*	6694	2.575	2.639	0.712	-0.223	3.856	0	5.165	9679	2.427	2.565	0.660	-0.372	3.611	0	4.997
size	6780	1.672	2	0.767	0.326	2.241	0	3	9776	1.468	1	0.709	0.505	2.838	0	3
partOFlarge	6780	0.095	0	0.293	2.763	8.633	0	1	9776	0.083	0	0.276	3.024	10.145	0	1
fowner	6699	0.057	0	0.233	3.803	15.461	0	1	9688	0.045	0	0.208	4.366	20.066	0	1
export	6695	0.353	0	0.478	0.613	1.376	0	1	9664	0.126	0	0.332	2.249	6.059	0	1
inno	6649	0.999	0	1.331	1.074	2.830	0	4	9657	0.812	0	1.233	1.343	3.538	0	4
rd	6707	0.152	0	0.359	1.935	4.742	0	1	9717	0.076	0	0.265	3.199	11.231	0	1
Ftech	6694	0.197	0	0.398	1.523	3.320	0	1	9660	0.120	0	0.325	2.341	6.478	0	1
ICT	6751	0.818	1	0.386	-1.644	3.703	0	1	9733	0.821	1	0.384	-1.670	3.790	0	1
workerskill	6436	27.838	20	27.671	1.160	3.417	0	100	9337	37.692	30	32.833	0.589	2.035	0	100
managerskill	6577	18.153	16	10.916	0.841	3.487	1	70	9485	16.146	15	9.719	0.957	4.243	1	100

Source: author calculations based on BEEPS V.

Table 9
Correlation matrix for total sample

	ln_lpro	ln_age	size	partOF large	fowner	export	inno	rd	Ftech
ln_*lpro*	1.0000								
ln_*age*	0.0642*	1.0000							
size	0.0651*	0.1869*	1.0000						
partOFlarge	0.0367*	0.0167	0.1086*	1.0000					
fowner	0.0920*	-0.0133	0.1040*	0.1484*	1.0000				
export	0.1034*	0.1402*	0.1793*	0.1077*	0.1561*	1.0000			
inno	0.1110*	0.0789*	0.0869*	0.0712*	0.0877*	0.1625*	1.0000		
rd	0.0885*	0.0700*	0.0915*	0.0585*	0.0606*	0.1972*	0.4192*	1.0000	
Ftech	0.0646*	0.0506*	0.0952*	0.1042*	0.1125*	0.1542*	0.1396*	0.1308*	1.0000
ICT	0.1672*	0.0491*	0.1251*	0.0455*	0.0619*	0.0844*	0.1556*	0.0863*	0.1021*
workerskill	0.0346*	-0.1708*	0.0061	0.0048	0.0105	-0.1304*	0.0373*	0.0138	-0.0055
managerskill	0.0720*	0.4037*	0.0416*	-0.0047	-0.0390*	0.1163*	0.0503*	0.0571*	0.0491*

	ICT	worker skill	manager skill
ICT	1.0000		
workerskill	0.0992*	1.0000	
managerskill	-0.0139	-0.1741*	1.0000

*p < 0.01

Source: author calculations based on BEEPS V.

Figure 1
Productivity differences: Kernel distribution of log labour productivity for EU and non-EU countries and for manufacturing and service sectors

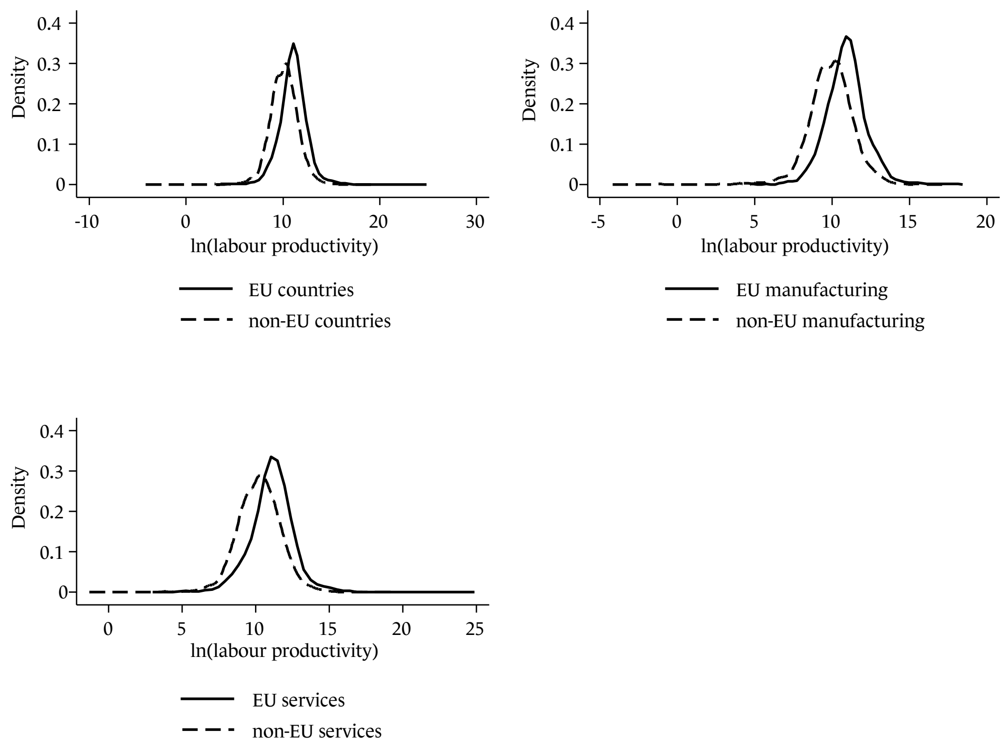
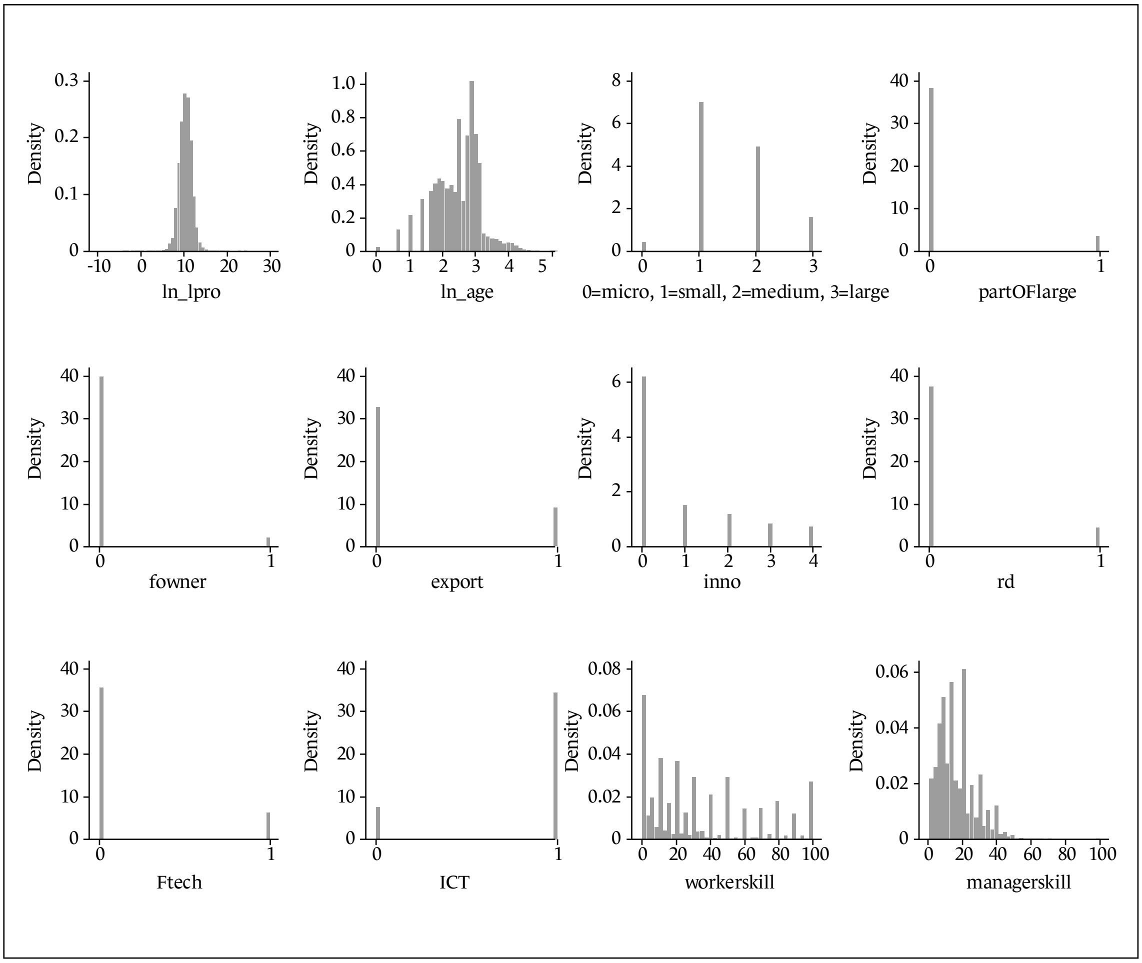


Figure 2
Histograms of variables' distributions



Source: author elaboration based on BEEPS V.