Resource misallocation and production inefficiency
Estimating cross-country differences in macroeconomic performance

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Abstract
Purpose – Recent studies have linked differences in aggregate productivity to misallocation of resources across firms. In contrast, the purpose of this paper is to study the macroeconomic performance of OECD economies from a production efficiency point of view and estimated the determinants of (in)efficiency with particular emphasis on misallocation of labor.

Design/methodology/approach – Following the pioneering work of Battese and Coelli, the authors proposed a parametric methodology to construct a world frontier that serves as a benchmark to compare the relative position of each country. The non-negative technical inefficiency effects are assumed to be a function of explanatory variables. By doing this, determinants of technical inefficiency are explicitly introduced in the model.

Findings – The results revealed that OECD countries to operate efficiently should expand their aggregate output by 22.6 percent without consuming more resources. A novel finding is that higher skill mismatch is associated with higher production inefficiency. Conversely, more flexible labor markets, and better management and human resource practices, lowered the inefficiency in production. The paper also analyzed the underlying factors driving skill misallocation in the job market. In this regard, a well-functioning education and training system and greater flexibility in the determination of wages are associated with lower levels of mismatch between the skills of individuals and those required by the jobs.

Practical implications – The measurement of the productive efficiency of an economy (or country) is crucial to governments. It is important to know how far a given economy can be expected to increase its output by simply increasing its efficiency, without absorbing further resources. In other words, it is relevant to know if a country could produce more with the same resources and, therefore, could increase per capita income and welfare. In this type of analysis what also matters is to identify what factors or variables explain that greater or lesser ability of a country to convert its resources into aggregate production.

Originality/value – Much research on efficiency measurement has focused on the firm or industry level, mainly to study the efficiency of financial institutions. Efficiency studies using aggregated data across countries are rare in the literature of efficiency. This paper aimed to contribute to filling that shortage evaluating the macroeconomic performance of a sample of OECD countries from the production efficiency point of view.

Keywords Stochastic frontier analysis, OECD countries, Labour market characteristics, Production efficiency, Resource misallocation, Skill mismatch

Paper type Research paper

Introduction
Economics is the science which studies the way a society uses scarce resources such as labor and physical capital to produce goods and services to maximize social well-being. Economic efficiency is the situation in which it is impossible to generate a larger total welfare from the available resources. Regarding the standard production possibilities model, efficient positions are represented by points on the production possibilities curve where the

JEL Classification — E23, D20
The author of this paper has not made their research data set openly available. Any enquiries regarding the data set can be directed to the corresponding author.
maximum number of goods and services are produced from all available resources – and they are at their best use – and technology[1]. However, if resources are not optimally allocated because they are not at their best use (e.g. over-education), this misallocation of resources will cause society to be at inner points of its production frontier. Efficiency in production would improve if workers were assigned to jobs for which they have the right skills. The improvement in labor productivity, through the correct allocation of workers to their jobs, would move an economy to its production possibilities frontier. Efficiency gains translate into higher output and, ultimately, higher per capita income and welfare.

This paper is framed in the recent literature on the effects of the misallocation of resources on productivity, which is defined as a departure from the optimal allocation of resources (Andrews and Cingano, 2014; Bartelsman et al., 2013; Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008). In contrast to these studies, which have linked differences in aggregate productivity to the misallocation of resources across firms, this paper aimed to study the macroeconomic performance of OECD economies from a production efficiency point of view and to estimate the determinants of (in)efficiency with particular emphasis on misallocation of labor.

Although both terms, productivity and efficiency, are related, the concept of productivity is more general. Productivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use (OECD, 2001). For example, labor productivity can be defined as the quantity of output produced with a given level of labor input, irrespective of the quantity of other inputs used. The concept of total factor productivity (TFP) represents the ratio of output to an index of a combination of inputs, usually labor and capital[2]. Conversely, the concept of efficiency is related to the manner in which resources are used in the production. Full efficiency, in an engineering sense, means that a production process has achieved the maximum amount of output that is physically achievable with current technology, and given a fixed amount of inputs (OECD, 2001). If a society (or an economy) is achieving the best possible production in a given period, with existing technology and using all available resources which are at their best use, then it makes an efficient use of scarce resources. The maximum possible output becomes relevant in this paper to answer specific economic questions such as the efficiency of OECD economies and to identify the factors which explain differences in (in)efficiency. In this paper, our central hypothesis was that productive inefficiency of OECD countries is strongly affected by their misallocation of resources, mostly skills on the labor market.

Much research on efficiency measurement has focused on the firm or industry level, mainly to study the efficiency of financial institutions (e.g. Mia and Soltane, 2016). Efficiency studies using aggregated data across countries are rare in the literature of efficiency[3]. This paper aimed to contribute to filling that shortage evaluating the macroeconomic performance of a sample of OECD countries from the production efficiency point of view. The measurement of the productive efficiency of an economy (or country) is crucial to governments. It is important to know how far a given economy can be expected to increase its output by simply increasing its efficiency, without absorbing further resources. In other words, it is relevant to know if a country could produce more with the same resources and, therefore, could increase per capita income and welfare. In this type of analysis what matters too is to identify what factors or variables explain that greater or lesser ability of a country to convert its resources into aggregate production.

One of the contributions of this paper is precisely the introduction of an empirical strategy that is robust to those concerns. Frontier functions provided the basis for defining efficient performance. Our proposed model is a stochastic frontier version of Battese and Coelli (1995) which includes both a stochastic error term and a term that can be characterized as inefficiency. The non-negative technical inefficiency effects are assumed to be a function of explanatory variables. By doing this, determinants of technical inefficiency...
are explicitly introduced in the model. We got accurate estimates regarding the efficiency of aggregate production process across OECD countries and its determinants. Notably, the paper revealed that OECD countries, as an industry, to operate efficiently should simultaneously expand their aggregate output by 22.6 percent without consuming more resources. Among other actions, an increase in production could be achieved with an improved matching of skills to jobs. Our method for estimating determinants of inefficiency showed that the greater the resource misallocation (skill mismatch), the higher the inefficiency in production. Conversely, more flexible labor markets for hiring and firing of workers, and better management and human resource practices, lowered the production inefficiency across our set of countries. Suitable data are probably the most crucial prerequisite to supporting our results. We used OECD estimates based on the Survey of Adult Skills.

Why should be concerned about skill mismatch? Mismatched individuals may suffer from lower wages and are less satisfied with their jobs than if they were properly matched; employers may suffer from lower productivity; and the economy may suffer from a loss of output (Cedefop, 2010). By allowing for the possibility that mismatch affects productivity through its impact on resource allocation, this paper connected research on mismatch to an emerging literature which has focused on resource misallocation as a potential explanation for why some countries are more productive than others. Needless to say that the goal of this paper is not to provide an exhaustive study of causal factors of inefficiency across OECD countries. We presented empirical results that demonstrated how our methodology could be useful to address issues of resource misallocation, after implementing some standard procedures to address some measurement issues and enhance cross-country comparability.

The rest of the paper is structured as follows. In the second section, we give an overview of the two primary methods used in the efficiency measurement literature: parametric and non-parametric. The third section presents the basic methodology proposed in this study. Following the pioneering work of Battese and Coelli (1995), we propose a parametric methodology to construct a world frontier that serves as a benchmark to compare the relative position of each country. Afterward, we described the data and variables in the fourth section. The results of several empirical analysis were reported in the fifth and sixth sections. The paper is concluded in the seventh section.

Background

Resource misallocation

Basic economics stresses the crucial role of resource allocation in achieving efficiency. Resource misallocation[4] is an essential source of productivity differences across countries (Restuccia and Rogerson, 2017). Resource misallocation arises when an economy features distortions implying that marginal product of inputs is not equated across productive units. In this case, an appropriate reallocation of production factors from low- to high-productivity producers would raise aggregate output (Andrews and Cingano, 2014). The notion that the allocation of inputs across establishments is a significant component of aggregate productivity is reinforced by research in the USA and elsewhere. These studies have found the reallocation of inputs from less- to more-productive establishments to be an important component of aggregate productivity growth (Foster et al., 2001; Restuccia and Rogerson, 2017). Considerable debate persists over the sources of this growth and the relative contributions of improvements in TFP vs the utilization of additional resources, particularly physical and human capital (Brandt et al., 2012). Increasing competitive pressure and the adoption of new technology are often mentioned as drivers of TFP growth (Brandt et al., 2012).

In the explanation of the aggregate productivity growth, Hsieh and Klenow (2009) asked how much larger the Chinese and Indian economies would be if they achieved the
same efficiency in allocating inputs across production units as does the USA. Other studies have found that productivity growth in an industry is dominated by entry and exit (Brandt et al., 2012; Foster et al., 2001). When new firms replace exiting firms, the reallocation of input factors tends to enhance efficiency since entering plants tend to have higher productivity than exiting plants. Direct subsidization and other forms of support for weak and failing enterprises may impede exit, while discriminatory taxes, bureaucratic interference and uncertain property rights protection may raise entry and investment costs, thus hindering entrepreneurship and the growth of more successful firms (Brown and Earle, 2008).

An additional justification for productivity differences lies in variations in management practices across establishments, firms and countries (Bloom and Van Reenen, 2007, 2010; Bloom et al., 2013), and in the allocation of talents. Hsieh et al. (2013) analyzed the effects of race and gender discrimination on the misallocation on talents and, through this, on productivity. They concluded that 15–20 percent of the growth in aggregate output per worker between 1960 and 2008 could be explained by the improved allocation of talent that followed a reduction in discrimination. In other words, declines in misallocation may explain a significant part of US economic growth during the last 50 years.

Research on these questions is still in its early stages. Until recently, data constraints have prevented empirical research from quantifying the magnitudes and contributions of reallocation. Comprehensive panel data on business units are required, for example, to measure the extent to which aggregate productivity growth is driven by productivity improvements within firms as opposed to resource reallocation from less to more productive firms (Brown and Earle, 2008; Brynjolfsson and Hitt, 2003).

Misallocation of labor
The Survey of Adult Skills is the main output of the Programme for the International Assessment of Adult Competencies run by the OECD in collaboration with national governments. The OECD Survey of Adult Skills (PIAAC) includes a rich battery of questions on skill use at work and direct indicators of workers’ skill proficiency derived from a purposely designed assessment exercise. The indicators of skill and qualification mismatches described and used in this paper were officially adopted by the OECD (2016). The survey provides a rare opportunity to simultaneously measure skill and qualification mismatch[5]. Skill mismatch arises when workers have higher or lower skills proficiency than that required by their job. If their skills proficiency is higher than that required by their job, workers are classified as over-skilled; if the opposite is true, they are classified as under-skilled[6]. Likewise, qualification mismatch arises when workers have an educational attainment that is higher or lower than that required by their job. If their qualification level is higher than that required by their job, workers are classified as over-qualified; if the opposite is true, they are classified as under-qualified (OECD, 2016).

On average, 14.8 percent of workers were classified as skill mismatched and 34.6 percent as qualification mismatched across 26 OECD countries covered by the survey (Table I)[7]. Figures 1 and 2 show the percentage of mismatched workers, by type of mismatch, for each country. For example, over-skilling can affect as many as 27.8 percent of workers in Greece and as few as 5.8 percent in Sweden. Under-skilling is the lowest in Austria (1.3 percent) and Germany (1.4 percent) and is the highest in Chile (9.9 percent). The prevalence of qualification mismatch also varies significantly across countries. Over-qualification is the largest in New Zealand (33.8 percent), France (31.3 percent) and Japan (31.1 percent); by contrast, the least prevalence of this type of mismatch is found in Slovenia (11.8 percent) and Turkey (11.6 percent). The incidence of under-qualification is the lowest in the Czech Republic (7.8 percent) and Japan (8.0 percent) and the highest in Italy (22.4 percent) and Sweden (21.2 percent).
According to Figures 1 and 2, there is still considerable room for efficiency improvement in human capital allocation in the OECD. While it is essential to have an education and training system that ensures that adults develop the skills needed in the labor market, it is also important that the labor market matches workers to jobs in which they can put their human capital to the best use. A mismatch between workers’ skills and the demands of their employment has potentially significant economic implications. At the macroeconomic level, it reduces GDP growth through the waste of human capital and the implied reduction in productivity (OECD, 2016).

The existing literature, typically, does not estimate the direct effect of mismatch on productivity, but instead infers it indirectly from wages, job satisfaction and other correlates of productivity (Hartog, 2000). However, recently, Adalet-McGowan and Andrews (2015, 2017), using PIAAC data, have found that higher skill mismatch was associated with lower labor productivity through a less efficient allocation of resources. Consequently, reducing skill mismatch emerges as a new channel through which well-designed framework policies can boost labor productivity.

Likewise, very few empirical studies have looked at the determinants of skill mismatch, mostly because of the difficulty in identifying and collecting data on a suitable cross-country longitudinal measure of mismatch as the dependent variable. Approaches that emphasize the

Table I. Variables and descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Obs</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Output/inputs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>Total GDP in 2013</td>
<td>26</td>
<td>1.64E+12</td>
<td>3.10E+12</td>
<td>3.28E+10</td>
<td>1.58E+13</td>
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<tr>
<td>CAPITAL</td>
<td>Aggregate capital stocks in 2013</td>
<td>26</td>
<td>3.59E+12</td>
<td>7.03E+12</td>
<td>3.56E+10</td>
<td>3.10E+13</td>
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<tr>
<td>LABOR</td>
<td>Total working hours in 2013</td>
<td>26</td>
<td>3.29E+10</td>
<td>5.18E+10</td>
<td>1.12E+09</td>
<td>2.53E+11</td>
</tr>
<tr>
<td>HUMAN CAPITAL</td>
<td>Higher education</td>
<td>26</td>
<td>22.81</td>
<td>6.68</td>
<td>11.20</td>
<td>35.57</td>
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<td>PROPERTY_RIGHTS</td>
<td>Property rights</td>
<td>26</td>
<td>5.17</td>
<td>0.77</td>
<td>3.83</td>
<td>6.33</td>
</tr>
<tr>
<td>TECHNOLOGY</td>
<td>Availability of latest technologies</td>
<td>26</td>
<td>5.92</td>
<td>0.53</td>
<td>4.43</td>
<td>6.55</td>
</tr>
<tr>
<td><strong>Explanatory variables</strong></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>SKILL_MISMATCH</td>
<td>Skill mismatch</td>
<td>26</td>
<td>14.81</td>
<td>5.59</td>
<td>9.58</td>
<td>34.37</td>
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<td>QUALIFICATION_MISMATCH</td>
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<td>34.58</td>
<td>6.22</td>
<td>22.40</td>
<td>44.44</td>
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<tr>
<td>HIRING_PRACTICES</td>
<td>Hiring and firing practices</td>
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<td>3.56</td>
<td>0.77</td>
<td>2.37</td>
<td>5.05</td>
</tr>
<tr>
<td>DELEGATION_AUTHORITY</td>
<td>Willingness to delegate authority</td>
<td>26</td>
<td>4.60</td>
<td>0.86</td>
<td>3.09</td>
<td>6.01</td>
</tr>
</tbody>
</table>

Notes: 
- Output/inputs not in logarithms;
- GDP: gross domestic product (expenditure approach), US dollar, constant prices 2010, constant PPPs (Source: OECD.Stat);
- Aggregate capital stocks estimates for 2011 (last year available), in USD of 2000, using the perpetual inventory method (PIM) (Source: Berlemann and Wesselhoft (2014) www.michael-berlemann.de/data);
- Total working hours in 2013 (Source: OECD.Stat);
- Willingness to delegate authority to subordinates (1 = not willing at all – senior management takes all important decisions; 7 = very willing – authority is mostly delegated to business unit heads and other lower-level managers) (Source: The Global Competitiveness Report 2013–2014 (World Economic Forum, 2013)).
supply side of the labor market in modeling labor market functioning as it pertains to skills, skill use and skill development tend to portray skill mismatch as a phenomenon driven by supply-side conditions. From this perspective, mismatch tends to be attributed to the inadequacies of the education and training system (Desjardins and Rubenson, 2011). Overall, education and training systems should ensure quality and be made to be more responsive to the needs of the job market.

In contrast, approaches that emphasize the demand side of the labor market tend to portray skill mismatch as a phenomenon driven by demand-side conditions. From this perspective, mismatch tends to be attributed to the inadequacies of labor market practices and of employers to identify and correct for mismatch, either via the provision of additional education, or in terms of adjusting work and organizational practices in ways that optimize skill use (Desjardins and Rubenson, 2011).
Methodology

Introduction

The analysis of the production efficiency of industrialized countries, questioning whether certain countries perform better than others in producing more output with the same or fewer inputs, is an example of the importance of estimating production relationships (Emrouznejad, 2003). In this regard, frontier functions provide the basis for defining efficient performance. A production frontier specifies maximum output for a given set of inputs and existing production technology. We propose a parametric method to construct a world frontier that serves as a benchmark to compare the relative position of each country. Relative efficiency is measured by comparing observed performance against best-practice performance. A question of interest is whether production inefficiency occurs randomly across countries, or whether some countries have predictably higher levels of inefficiency than others. If the occurrence of inefficiency is not totally random, then it should be possible to identify factors that contribute to the existence of inefficiency.

In the following paragraphs, we set forth the basic frontier statistical models as suggested by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). We then modified these frontier models to include country-specific inefficiency factors as suggested by Battese and Coelli (1995).

Stochastic frontier econometric model

The stochastic frontier estimation method, developed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977), generates a production frontier with a stochastic error term that consists of two components: a conventional random error (white noise) and an asymmetric component that measures inefficiency. Formally, the basic stochastic frontier model is given by:

\[ y_i = f(x_i) + \varepsilon_i \]

where \( y_i \) is the production (output) of the producer \( i \), \( x_i \) is the vector of factors or resources used in production, \( f() \) is a measurable production function and \( \varepsilon_i \) is an error term which is composed of two separate elements \( v_i \) and \( u_i \), so that:

\[ \varepsilon_i = v_i - u_i. \]

The component \( v_i \) collects those production variations due to random factors beyond the control of the producer. The model assumes that each \( v_i \) is distributed as a normal random variable with mean zero and variance \( \sigma_v^2 \). The \( u_i \) component represents the technical efficiency (TE) relative to the stochastic frontier and takes only positive values (\( u_i \geq 0 \)). The original model assumes that each \( u_i \) is distributed independently as a skewed distribution, half-normal with zero mean and variance \( \sigma_u^2 \). TE is total when \( u_i = 0 \), and there is technical inefficiency if \( u_i > 0 \), regardless of the value taken by \( v_i \).

The indices of TE for each country \( i \) can be calculated as:

\[ TE_i = e^{-u_i}, \]

where \( 0 < TE_i \leq 1 \). A country or economy will be fully efficient provided that TE is worth 1. Industry efficiency can be viewed as the average of the efficiencies of all the producers in the industry. Thus, a natural predictor of industry efficiency is the average of the predicted efficiencies of the producers in the sample (Coelli et al., 2005).
One-step maximum likelihood estimates procedure
This paper used a stochastic frontier production function defined for cross-sectional data on countries in which the non-negative technical inefficiency effects are assumed to be a function of country-specific variables. Our proposed model of the production and inefficiency is a stochastic frontier version of Battese and Coelli’s (1995) and is given by equation (1), the stochastic production frontier, and equation (2), the inefficiency function [8]. The inefficiency effects are assumed to be independently distributed as truncations of normal distributions with constant variance, but with means which are a linear function of observable variables.

The first equation specifies the stochastic frontier production function. A Cobb–Douglas production function for one output and K inputs would be specified as follows [9]:

$$\ln y_i = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{ki} + v_i - u_i,$$  \hspace{1cm} (1)

where $y_i$ denotes the production of the $i$th country, $x_i$ is a vector of input quantities of the $i$th country and $\beta$ is a vector of unknown parameters to be estimated. The $v$ term takes care of the stochastic nature of the production process and possible measurement errors of the inputs and output, and the $u$ term is the possible inefficiency of the producer; $v_i$s are assumed to be iid $N(0, \sigma^2_v)$ random errors independently distributed of the $u_i$s. It is also assumed a truncated-normal distribution for the inefficiency term [10]:

$$u_i \sim \text{iidN}^+ (\mu, \sigma^2_u) \text{ (truncated-normal)}.$$  

The second equation captures the effects of technical inefficiency. To investigate the existence of systematic influences on the inefficiency disturbances, we incorporate country-specific effects into the model of the inefficiency error. The model for inefficiency effects for cross-sectional data would be specified as:

$$\mu_i = z_i \delta + \omega_i,$$  \hspace{1cm} (2)

where $z_i$ is a vector of explanatory variables determining the technical inefficiency of production, and $\delta$ is a vector of unknown coefficients to be estimated and is defined by the truncation of the normal distribution $N(0, \sigma^2_\delta)$.

Data and variables
Output and inputs in equation (1)
Efficiency measurement requires quantitative information on inputs and output of the process. Table I summarizes the explanatory variables used in equation (1) and presents the descriptive statistics. On the one hand, regarding the output, national accounts measure the performance of entire economies in the commonly quoted measure gross domestic product. In this paper, the variable GDP was used as a proxy for economic results of OECD countries. On the other hand, many models of growth and development assume that output is generated by a two-factor, Cobb–Douglas specification for the aggregate production function with physical capital and labor serving as inputs (Duffy and Papageorgiou, 2000). In equation (1), we considered the inputs CAPITAL and LABOR.

In connection with the labor input, from a perspective of production analysis, the quantity of labor is most appropriately measured as the total number of working hours (OECD, 2001). Simple headcounts of employed persons will hide changes in average working hours, caused by the evolution of part-time employment or the effect of variations in overtime, absence from work or shifts in regular hours. However, it would be desirable the differentiation of labor input by skill category. Because a worker’s contribution to the...
production process consists of his/her “raw” labor (or physical presence) and services from his/her human capital, 1 h work completed by one person does not necessarily constitute the same amount of labor input as 1 h work completed by another person. There may be differences in skills, education and professional experience that lead to substantial differences in the contribution of different types of labor. A differentiation of labor input by type of skills is particularly desirable if one wants to capture the effects of a changing quality of labor on the growth of output and productivity. We have included in our analysis the variable HUMAN_CAPITAL.

We also used two extra variables that approximate the production technology: PROPERTY_RIGHTS and TECHNOLOGY. Efficiency analyzes traditionally assume that production technology is similar across producers. However, there are some problems in making cross-country comparisons because there are differences in how the production processes are implemented in the firms. Although OECD countries enjoy a high degree of political, social and cultural similarities, they may differ from one another in their technological readiness which measures the agility with which an economy adopts existing technologies to enhance the productivity of its industries (Sala-i-Martin et al., 2011). Some firms use the latest and best technology, while others use more traditional methods (Bartelsman and Doms, 2000)[11].

Explanatory variables in equation (2)
Traditional efficiency studies measure the performance of a producer by its ability to transform inputs into outputs. However, the actual way in which these inputs are transformed into outputs is often overlooked (Frei and Harker, 1999). In this paper, explanatory variables in equation (2) provide the opportunity to analyze this “black box” in terms of identifying the performance of the process. The identification of the factors that explain differences in efficiency across OECD economies is essential for improving the results of the countries. Indeed, the influence of process/contextual variables on the production efficiency has been a major topic of economic research primarily for managers and policy makers (e.g. Banker and Natarajan, 2008). In this paper, we focused mainly on the impact of country-specific labor market characteristics on productive efficiency. We hypothesized that three critical aspects of a labor market, namely, misallocation of labor, the flexibility of the job market and human resource management (HRM) practices affect productive efficiency across OECD countries – the term efficiency refers to the process by which resources are optimized in production.

Table I also summarizes the explanatory variables used in equation (2) and presents the descriptive statistics. The first two variables are SKILL_MISMATCH and QUALIFICATION_MISMATCH. Our initial hypothesis is that a higher mismatch between skills and qualifications is demanded by the jobs and those possessed by workers will increase the inefficiency of the production process due to lower labor productivity. Indeed, recent research has shown that a higher skill mismatch is associated with lower labor productivity through a less efficient allocation of resources (Adalet-McGowan and Andrews, 2017). On the contrary, higher labor market flexibility in hiring and firing workers (peroxide by the variable HIRING_PRACTICES), as well as better HRM practices (peroxide by the variable DELEGATION_AUTHORITY), can be expected to improve productivity and efficiency (or reduce inefficiency). In this regard, Foster et al. (2001) showed how entrepreneurial and managerial ability lead to differences in job and productivity growth rates among firms and plants. These differences included the ability to identify and develop new products, to organize production activity, to motivate workers and to adapt to changing circumstances. Other labor economists have also explored the importance various managerial and human resource practices in explaining workers' productivity differences (e.g. Bloom and Van Reenen, 2007, 2010, 2011). Of the four independent variables, only the variables SKILL_MISMATCH and DELEGATION_AUTHORITY are correlated but it is a moderate correlation.
Results of efficiency analysis

Following Battese and Coelli (1995), the stochastic frontier production function and the technical inefficiency effects model must be jointly estimated by maximum likelihood. We derived maximum likelihood estimates of the parameter vectors \( \beta \) and \( \delta \) from the simultaneous estimation of the production function and inefficiency term equations, equations (1) and (2), using the Stata14 statistical package. This software allows us to use the one-stage procedure when a truncated-normal distribution is specified. The results were shown in Table II.

First, in relation to the estimation of the frontier production function, only the estimated coefficients associated with the capital and labor inputs have shown statistical significance and with the expected sign. And being both the dependent variable and the independent variables in logarithms, the estimated coefficients measure the elasticity of output concerning capital and labor inputs. We got output elasticities of capital and labor as 0.5351 and 0.4617, respectively. In other words, in the period of study, holding the labor input constant, a 1 percent increase in the capital input led, on average, to a 0.5351 percent increase in the output. Similarly, keeping the capital input constant, a 1 percent increase in the labor input led, on average, to a 0.4617 percent increase in the output.

Second, the average efficiency in the OECD was 84.5 percent (last row in Table II); this finding indicates that OECD countries, as an industry, to operate efficiently should simultaneously expand their output by 22.6 percent keeping their inputs fixed[12].

Third, the estimates of our analysis inform us of which country-specific factors impact the efficiency in production. According to Table II, countries' ability to expand their output could be achieved through better job matches, more flexible labor markets, as well as by process and organizational innovations such as better business practices. More specifically, the results confirm that those OECD countries with a higher skill mismatch tend to be more inefficient. In contrast, those countries with more flexible labor markets for hiring and firing of workers and better human resources practices tend to be less inefficient[13]. Therefore, when asked whether or not variations in HRM practices play a role in driving differences in

<p>| A Cobb–Douglas production function/truncated-normal distribution for the inefficiency term |
|-----------------------------------------------|-----------|-----------|</p>
<table>
<thead>
<tr>
<th>Coef.</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln (CAPITAL)</td>
<td>0.5351**</td>
</tr>
<tr>
<td>ln (LABOR)</td>
<td>0.4617**</td>
</tr>
<tr>
<td>ln (HUMAN_CAPITAL)</td>
<td>−0.1826</td>
</tr>
<tr>
<td>ln (PROPERTY_RIGHTS)</td>
<td>−0.6264</td>
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<tr>
<td>ln (TECHNOLOGY)</td>
<td>−0.3247</td>
</tr>
<tr>
<td>Constant</td>
<td>3.8933**</td>
</tr>
</tbody>
</table>

Technical inefficiency function

<table>
<thead>
<tr>
<th>Coef.</th>
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<tr>
<td>SKILL_MISMATCH</td>
<td>0.0243**</td>
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<tr>
<td>QUALIFICATION_MISMATCH</td>
<td>−0.0023</td>
</tr>
<tr>
<td>HIRING_PRACTICES</td>
<td>−0.2633**</td>
</tr>
<tr>
<td>DELEGATION_AUTHORITY</td>
<td>−0.1438*</td>
</tr>
<tr>
<td>Constant</td>
<td>1.3648**</td>
</tr>
<tr>
<td>Number of obs</td>
<td>26</td>
</tr>
<tr>
<td>Wald ( \chi^2 )(5)</td>
<td>3,423.40</td>
</tr>
<tr>
<td>Prob &gt; ( \chi^2 )</td>
<td>0.0000</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>18.435414</td>
</tr>
<tr>
<td>Average efficiency</td>
<td>0.8447</td>
</tr>
</tbody>
</table>

Notes: \(^*\)Output = ln (GDP), \(^*,**,\)Significant at 10 and 5 percent levels, respectively
efficiency and productivity, we find that the answer is “probably, yes.” Decentralization of decision-making may increase productivity through rising job satisfaction. Delegation of responsibility goes along with more employee involvement, greater information sharing and a greater participation of lower level staff (Bloom and Van Reenen, 2011).

Hypothesis testing
The appropriateness of the stochastic frontier approach should be tested for the absence of inefficiency effects (the null hypothesis):

\[ H_0 = \text{There is no component of inefficiency in the composite error.} \]

A likelihood-ratio (LR) test can be used to this end. In the case of the truncated-normal model, the null hypothesis \( H_0: \mu = \sigma_u^2 = 0 \) should be rejected at the 5 percent level of significance if the LR test statistic exceeds 5.138 (Coelli et al., 2005). We computed LR = 10.450 which exceeds 5.138, so we reject the null hypothesis of no technical inefficiency effects, increasing therefore the credibility of the estimated stochastic frontier models.

Determinants of skill mismatch
In an attempt to describe the mismatch, we returned to our broad mismatch measure and estimated their determinants. The relationship between the skill mismatch \( Y \) and the explanatory variables \( X \) that influence the incidence of skill mismatch at the aggregate level is evaluated based on the results of the regression:

\[ Y_i = \alpha + X_i \beta + \varepsilon_i \quad i = 1, 2, \ldots, 26. \] (3)

In equation (3), \( \alpha \) denotes the intercept, \( X \) is a vector of labor market variables – supply and demand sides of the labor market –, \( \beta \) is the coefficient which needs to be estimated and \( \varepsilon \) is error term.

First, about supply-side variables of the labor market, a well-functioning education and training system should be associated with lower levels of persistent mismatch between the skills of individuals and those required by the labor market (Quintini, 2011). We considered the quality of education and training: EDUCATION_TRAINING (Table III).

Second, the institutional framework regulating the labor market is regarded by most researches as an essential dimension in explaining the difficulties of some economies in adapting to changing conditions (Quintini, 2011). Labor market institutions that hamper those adjustments are likely to worsen skill mismatch; thus, unionization is positively correlated with skill mismatch, but coordination in wage bargaining reduces mismatch (Quintini, 2011). In our analysis, two demand-side variables of the labor market have been

<table>
<thead>
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<th>Variable</th>
<th>Description</th>
<th>Obs</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDUCATION_TRAINING</td>
<td>5th pillar of The Global Competitiveness Indexa</td>
<td>26</td>
<td>5.37</td>
<td>0.44</td>
<td>4.29</td>
<td>6.27</td>
</tr>
<tr>
<td>WAGE_DETERMINATION</td>
<td>Flexibility of wage determinationb</td>
<td>26</td>
<td>4.54</td>
<td>1.08</td>
<td>2.39</td>
<td>6.05</td>
</tr>
<tr>
<td>PAY_PRODUCTIVITY</td>
<td>Pay and productivityc</td>
<td>26</td>
<td>4.08</td>
<td>0.57</td>
<td>2.76</td>
<td>4.92</td>
</tr>
</tbody>
</table>

taken into account in the estimation of equation (3): WAGE\_DETERMINATION and PAY\_PRODUCTIVITY (Table III).

The results of the estimation of equation (3) are shown in Table IV. The estimated coefficients associated with two independent variables are negative and statistically significant. In particular, greater flexibility in wage determination and higher quality of education and training systems contributed to a better skill matching. Consequently, our empirical analysis of the underlying factors driving skill misallocation in the job market confirmed that both demand-side and supply-side factors affected the proportion of adults who were mismatched in the OECD. Although demand-side variables – flexibility of wage determination – can explain some of the observed skill mismatch patterns across OECD countries, the differences between countries in the quality of education and systems of on-the-job training also contributed to explaining differences in mismatch. We confirm, therefore, our working hypotheses based on the work of Quintini (2011).

What can OECD economies do to improve matching? In countries such as Spain and Greece, with a significant percentage of college graduates but also high unemployment rates, most educated people are probably the first to be placed in the queue of unemployment and the first even to be selected by employers. However, in the end, they end up in the positions where they are over-qualified. Therefore, Lester Thurow’s theories of competition for jobs in the 1970s remain valid somehow. Maybe, the solution will be in creating more managerial jobs where the qualifications of the educated workforce could be optimized. Also, encouraging a higher mobility of workers between industries and countries. A competitive labor market would have the flexibility to transfer workers from one sector to another quickly and at low costs. However, unlike the USA, there are barriers to labor mobility in Europe. It points to the possibility that the European single labor market is failing to play its role in allocating scarce resources (Figure 3)[14].

### Conclusion

The problem of resource allocation occupies a central position in economic theory. This paper evaluates the macroeconomic performance of a sample of OECD countries from the production efficiency point of view; that is, their ability to operate close to, or on the boundary of their production set. It is essential to know how far a given economy can be expected to increase its output by merely improving its efficiency, without absorbing further resources. Simultaneously, we examine the influence of process/contextual variables that explain OECD countries’ efficiency differences.

In their process of converting inputs into aggregate production, the term efficiency was identified to the way by which capital and labor inputs are optimized in production, after controlling for their production technologies and quality of labor. Our proposed model for

<table>
<thead>
<tr>
<th></th>
<th>Coef.</th>
<th>Robust SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDUCATION_TRAINING</td>
<td>−8.3465**</td>
<td>3.1760</td>
</tr>
<tr>
<td>WAGE_DETERMINATION</td>
<td>−2.4252**</td>
<td>0.9801</td>
</tr>
<tr>
<td>PAY_PRODUCTIVITY</td>
<td>1.5456</td>
<td>2.5604</td>
</tr>
<tr>
<td>Constant</td>
<td>64.2988**</td>
<td>20.4096</td>
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<tr>
<td>Number of obs</td>
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<tr>
<td>F(3, 22)</td>
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</tr>
<tr>
<td>Prob &gt; F</td>
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</tr>
<tr>
<td>$R^2$</td>
<td>0.3047</td>
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</tr>
</tbody>
</table>

**Notes:** Dependent variable: SKILL\_MISMATCH. The tolerance values (1/VIF) were greater than 0.2 for each independent variable. We conclude that we have no problem with multicollinearity (Mehmetoglu and Jakobsen, 2016). **Significance at 5 percent level

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Table IV. Determinants of skill mismatch
efficiency measurement is a stochastic frontier version of Battese and Coelli (1995) which includes both a stochastic error term and a term that can be characterized as inefficiency. The non-negative technical inefficiency effects are assumed to be a function of explanatory variables. The results from the stochastic frontier analysis reveal that OECD countries, as an industry, to operate efficiently should simultaneously expand their aggregate output by 22.6 percent without consuming more resources. Our methodology for estimating determinants of inefficiency shows that the greater resource misallocation – skill mismatch – the higher the inefficiency in production. Conversely, more flexible labor markets for hiring and firing of workers, and better management and human resource practices, lowered the inefficiency in production. The paper also examines the underlying factors driving skill misallocation in the labor market. In this regard, a well-functioning education and training system and greater flexibility in the determination of wages in the labor markets are associated with lower levels of mismatch between the skills of individuals and those required by the jobs.

Notes
1. Efficiency can also be defined in a dynamic sense as the rate at which the production possibility curve moves out overtime.
2. See Syverson (2011) for an extensive review on productivity, its measurement and its determinants.
3. We found some exceptions but using non-parametric methods (Färe et al., 1994; Arcelus and Arocena, 2000). We were not able to find any article that used parametric methods like that used in the present paper.
4. See Restuccia and Rogerson (2017) for a recent literature review on the causes and costs of misallocation.

5. The survey is a collection of country-specific household samples designed to be representative of the adult population aged between 16 and 65 years.

6. The measurement of skill mismatch is derived following Pellizzari and Fichen (2013). It focuses on information-processing skills.

7. Unfortunately, we had to discard Israel and the Slovak Republic by not having information on the stock of capital, key input in the analysis made in this paper.

8. Parameters, in both equations, are estimated simultaneously by maximum likelihood.

9. The choice of the distributional specification is sometimes a matter of computational convenience; theoretical considerations may also influence the choice of the distributional specification (Coelli et al., 2005).

10. The truncated-normal frontier model is due to Stevenson (1980).

11. In relation to land input, it has not been finally considered in the analysis. The information provided by the World Bank only addresses the percentage of arable land in a country, but we do not know what part of this input is ultimately earmarked for production.

12. To obtain this percentage, we must calculate the inverse of the efficiency scores for each country, and then calculate the mean. The result is 1.226.

13. Notice that a negative (positive) regression coefficient on the technical inefficiency function would mean that due to the rise of the independent variable, inefficiency decreases (increases).

14. Figure 3 is constructed with the answers of 4,488 European employers with at least 50 workers (66 percent of the total sample). The graph shows the percentage of employers surveyed in each country who mentioned language barriers and the lack of necessary skills as the main reasons for the question: “What is your reason for NOT recruiting graduates from other countries?” Multiple answers are possible.

References


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