Empirical Economics
https://doi.org/10.1007/s00181-020-01966-5

Persistent and transient inefficiency in adult education

Oleg Badunenko[1] · **Deni Mazrekaj**[2,3] · **Subal C. Kumbhakar**[4,5] · **Kristof De Witte**[3,6]

Received: 26 February 2020 / Accepted: 18 October 2020

Abstract

This paper evaluates the inefficiency of adult education programs. Using an advanced four-component stochastic frontier model on Belgian adult education data, we distinguish between persistent and transient inefficiency of adult education programs. Whereas persistent inefficiency is structural and difficult to tackle because of its time-invariant nature, transient inefficiency can be eliminated somewhat easily without a major structural change. Thus, reduction in different inefficiency components may require different policy measures. Our results indicate that despite the presence of persistent inefficiency, the overall inefficiency is mainly driven by the transient component, and hence, at the control of the adult education management. The findings suggest that social interaction is relevant in adult education as both more sessions and more learners per program increase educational efficiency. Moreover, adult education programs seem to be particularly useful for young less-educated learners.

Keywords Stochastic frontier analysis · Adult education · Inefficiency · Four-component model

JEL classification C54 · I21 · I28

1 Introduction

A highly skilled and well-trained workforce is essential for economic growth (Hanushek and Woessmann 2008). Yet, about 14% of the adult population aged 25 to 64 dropped out of high school in the OECD countries in 2017 (OECD 2020). According to the European Commission (2011), each percentage point reduction in high school dropout would lead to about half a million additional qualified employees.

The data for this study are protected by a confidentiality agreement and we are precluded from sharing the data with others. Interested readers can contact the corresponding author for information on how to obtain access to the data and the code.

Extended author information available on the last page of the article

Published online: 04 November 2020

Given the importance of a qualified workforce and given the relatively high dropout rates, most countries have introduced adult education to reintegrate school dropouts in the education system and to retrain them for the labour market (OECD 2019). As adult education attracts an increasing share of the total education budget, it is particularly interesting to analyse its productive efficiency. Contrary to significant attention of scholars to the efficiency of the compulsory education system (see an overview by De Witte and Lopez-Torres 2017), evidence on the performance of adult education is rare (an exception is Schiltz et al. 2019).

This paper defines education production technology for adult education. Using a production function for education, we assess the performance of adult education and analyse the determinants of inefficiency differentials. Said otherwise, this study investigates whether adult education programs are able to transform budget resources into highest attainable academic outcomes.

Using an advanced four-component Stochastic Frontier (SF) model on adult education data from the Flemish community in Belgium, we disentangle the overall inefficiency of adult education programs into two parts: the persistent inefficiency and the transient inefficiency. The persistent inefficiency refers to a long-term or structural inability of an adult education program to attain the potential level of academic outputs. The persistent inefficiency might originate from the target population of the adult education program, which is harder to reach than students in compulsory education and which requires different approaches such as online-learning or smaller class groups. Transient inefficiency, on the other hand, is a short-run deficit, which an adult education program manager can eliminate swiftly without a major structural change. Such short-term inefficiency implies that program outputs may be at their potential level in the next time period, or they may be below their potential level again. Distinguishing between persistent and transient inefficiency of adult education programs is important as different types of inefficiency may require different policy measures.

Our results indicate that the overall inefficiency of adult education programs amounts to 12%, suggesting that, given the available resources, the outputs (measured by exam scores, class attendance rates, and exam participation) could increase by 12%. Decomposing the overall inefficiency reveals that about 5 percentage points of the inefficiency are on average due to structural differences between the programs, whereas about 7 percentage points are at the discretion of the adult education management. Digging in the determinants of inefficiency provides insights into how efficiency can be enhanced. In particular, we show that social interaction is relevant as both more sessions and more learners per program increase efficiency. Moreover, adult education programs seem to be particularly useful for young low educated learners, suggesting that adult education might play a crucial role as second chance education for young people.

Previous literature has primarily focused on the inefficiency of compulsory education (see De Witte and López-Torres (2017) for a review) and higher education (see Sneyers and De Witte (2017) for a review). To the best of our knowledge, only one paper has evaluated the inefficiency of adult education programs (Schiltz et al. 2019). Using a conditional and bias-corrected Data Envelopment Analysis (DEA) model on Belgian data, Schiltz et al. (2019) found that adult education programs could improve their efficiency by 4%, on average. Moreover, they observed that teacher and program characteristics explain inefficiency differentials between adult education programs. However, inefficiency was estimated as a single component, without considering whether this inefficiency is persistent and difficult to tackle, or whether it is transient and can be eliminated in the short-run. Other studies did separate inefficiency into several (mostly four) components but mainly focused on higher education (Agasisti and Gralka 2019; Gralka 2018; Salas-Velasco 2020; Titus et al. 2016) or areas outside of education (Filippini et al. 2018; Filippini and Hunt 2016; Heshmati et al. 2018).

Despite the lack of interest from the efficiency analysis literature in adult education, earlier literature has shown that adult education can result in increased labour market outcomes (Blanden et al. 2012; Martin et al. 2013). For example, using fixed effects models on the British Household Panel Survey, Blanden et al. (2012) showed that adult learning increased women's earnings by 10%, whereas their estimates for males seem to be driven by selection effects. In a meta-review focused on entrepreneurship education and training, Martin et al. (2013) found that this training leads to the development of a range of entrepreneurship competences with subsequent positive consequences on the labour market.

2 Empirical methodology

2.1 Modelling inefficiency

To evaluate the efficiency of the adult education program,[1] we follow Hanushek (1986) and employ an education production function which is extended to accommodate panel features. The educational technology that we assume uses one input, which is the cost of an adult education program. The results of knowledge production are academic outcomes approximated by multiple outputs, e.g. the exam score and exam participation. Not all programs are able to equally employ resources and thus some of them are less efficient than others in achieving the academic outputs.

In an education production function, outputs $\mathbf{y}$ are a result of utilising input $\mathbf{x}$. This is a multi-output production process and one way to analyse it is to formulate the radial distance function.[2] In output-based efficiency measurement, the output distance function (ODF) is defined as

$$D^0 = \max\{\theta : \mathbf{y}\theta \in P(\mathbf{x})\}, \tag{1}$$

[1] Note that efficiency is defined as the exponential of inefficiency (with a negative sign), i.e. if the production technology with a single output is defined as $\mathrm{y} = \mathrm{f(x)}e^{\mathrm{v}-\mathrm{u}}$, where $\mathrm{u} \geq 0$ is inefficiency, efficiency is defined as e^{-u}, which is bounded between 0 and 1. Inefficiency is often interpreted as a percentage shortfall of output and efficiency is $\log(u) \approx 1 - u$, especially for small u. Thus, if there are two inefficiency components, they can be added to obtain the overall inefficiency because both represent percentage shortfalls whereas the overall efficiency will be the product of two efficiencies.

[2] An alternative is to use a transformation function with either input- or output-oriented inefficiency (Kumbhakar, 2013).

where $P(\mathbf{x})$ is the outputs set, i.e. a set of outputs such that inputs-output combination is technologically feasible. The ODF is thus a function of input and outputs, viz.,

$$D^O = f(\mathbf{x}, \mathbf{y}; \boldsymbol{\beta}), \tag{2}$$

where $\boldsymbol{\beta}$ is a vector of parameters to be estimated once $f(\cdot)$ is specified parametrically. Since the ODF is homogeneous of degree 1 in feasible outputs vector $\mathbf{y}$, (2) can be rewritten as

$$D^O y_1^{-1} = f(\mathbf{x}, \tilde{\mathbf{y}}_{-1}; \boldsymbol{\beta}), \tag{3}$$

where $\tilde{\mathbf{y}}_{-1} = \left(\frac{y_3}{y_1}, \frac{y_2}{y_1}\right)$. Taking the logs of both sides of (3), we obtain

$$-\log y_1 = \log f(\mathbf{x}, \tilde{\mathbf{y}}_{-1}; \boldsymbol{\beta}) - \log D^O. \tag{4}$$

In a panel data setting, we assume that the overall distance to the frontier, ODF, contains a persistent and transient component. Thus, for program i in time period t, we write $\log D^O = u_{0i} + u_{it}$, where $u_{0i} \geq 0$ is persistent inefficiency and $u_{it} \geq 0$ is transient inefficiency. That is, the overall inefficiency is $u_{0i} + u_{it}$ and the overall efficiency is $e^{u_{0i}} \times e^{u_{it}}$. Adding a random error term v_{it}, which is assumed to be i.i.d. normally distributed, to the ODF in (4) to make it stochastic, and accounting for program heterogeneity by including v_{0i}, which is also assumed to be i.i.d. normally distributed, we obtain a four-component stochastic frontier model in an output distance function framework[3]

$$-\log y_{1,it} = \log f\left(\mathbf{x}, \tilde{\mathbf{y}}_{-1,it}, \mathbf{c}; \boldsymbol{\beta}\right) + v_{0i} + u_{0i} + v_{it} + u_{it}, \tag{5}$$

where we also control for variables that do not affect the frontier, e.g. gender and socioeconomic status. It is important to emphasise that we distinguish between persistent inefficiency and transient inefficiency.

2.2 Modelling determinants of inefficiency

Since our application focuses on explaining the differentials of the inefficiencies, we argue that both public servants and program providers are interested in knowing the factors that could influence persistent and transient inefficiency, and the magnitude of their marginal effects. Thus, some adult education programs are below their potential and we will seek to identify the determinants of such shortfall.

Although there are many ways to introduce determinants of inefficiency, we follow Badunenko and Kumbhakar (2017) and introduce them via the variance of the

[3] The four-component homoscedastic model has been applied to analyse the efficiency in health care, agriculture, transportation, and US banks (Colombi, Kumbhakar, Martini and Vittadini, 2014).

half-normal error terms used to represent inefficiency. That is, in the half-normal distribution, we specify the (pre-truncated) variance of u_{0i} which is time-invariant, viz.,

$$u_{0i} \sim N^{+}\left(0, \sigma_{u_{0i}}^{2}\right), \text{ where } \sigma_{u_{0i}}^{2} = \sigma_{u_0}^{2} \exp\left(\mathbf{z}_{u0i} \boldsymbol{\gamma}_{u0}\right), \quad i = 1, \ldots, n, \tag{6}$$

and $\mathbf{z}_{u0i}$ is the vector of covariates that form the inefficiency heteroskedasticity function, but at the same time, these covariates are determinants of persistent inefficiency. Since $E(u_{0i}) = \sqrt{\left(\frac{2}{\pi}\right)}\sigma_{u_{0i}} = \sqrt{\left(\frac{2}{\pi}\right)}\exp\left(\frac{1}{2}\mathbf{z}_{u0i}\boldsymbol{\gamma}_{u0}\right)$, the $\mathbf{z}_{u0i}$ variables can be viewed as determinants of persistent inefficiency. Consider Efficiency Change (EC) due to a change in z_{01} holding everything else fixed. Since the persistent efficiency is exp $(-u_{0i})$, the rate of change in it due to a change in z_{01} (labelled as EC) is given by

$$\text{EC} :\equiv \Delta A_i = -\frac{\partial u_{0i}}{\partial z_{01}} \approx -\frac{\partial E(u_{0i})}{\partial z_{0i}} = -\sqrt{\frac{2}{\pi}}\frac{\partial \sigma_{u_{0i}}}{\partial z_{0i}}. \tag{7}$$

Under the assumption $\sigma_{u_{0i}}^{2} = \exp\left(\mathbf{z}_{u0i}\boldsymbol{\gamma}_{u0}\right)$, Eq. (7) becomes

$$-\sqrt{\frac{2}{\pi}}\frac{1}{2}\gamma_{u01}\exp\left(\frac{1}{2}\mathbf{z}_{u0i}\boldsymbol{\gamma}_{u0}\right). \tag{8}$$

Variables in $\mathbf{z}_{u0i}$ vary across programs but are time-invariant. This means that $\sigma_{u_{0i}}^{2}$ is explained only by time-invariant covariates.

Similarly, we introduce determinants of time-varying inefficiency via the pre-truncated variance of u_{it}. That is, we assume

$$u_{it} \sim N^{+}\left(0, \sigma_{u_{it}}^{2}\right), \quad \text{where } \sigma_{u_{it}}^{2} = \sigma_{u}^{2}\exp\left(\mathbf{z}_{uit}\boldsymbol{\gamma}_{u}\right), \quad i = 1, \ldots, n, \quad t = 1, \ldots, T_i, \tag{9}$$

where $\mathbf{z}_{uit}$ denotes the vector of covariates that explains time-varying inefficiency. Since u_{it} is half-normal, $E(u_{it}) = \sqrt{\left(\frac{2}{\pi}\right)}\sigma_{u_{it}} = \sqrt{\left(\frac{2}{\pi}\right)}\exp\left(\frac{1}{2}\mathbf{z}_{uit}\boldsymbol{\gamma}_{u}\right)$, and therefore, anything that affects $\sigma_{u_{it}}$ also affects time-varying inefficiency. The marginal effects of time-varying determinants can be calculated using Eqs. (7) and (8) replacing $\mathbf{z}_{u0i}$ and $\boldsymbol{\gamma}_{u0}$ with $\mathbf{z}_{uit}$ and $\boldsymbol{\gamma}_{u}$, respectively.

2.3 The Empirical Model

Using the output distance function in (5), we test the appropriate functional form (see Sect. 4.1. Our final specification is a translog production function for one input (x_1) and three outputs (y_1, y_2, y_3). We include a nonlinear time trend to control for technological change over time:

$$-\log y_{1it} = \beta_0 + \sum_{p=2}^{3}\beta_p \log\left(\frac{y_{p,it}}{y_{1,it}}\right) + 0.5\sum_{p=2}^{3}\beta_{pp}\left[\log\left(\frac{y_{p,it}}{y_{1,it}}\right)\right]^2$$

$$+ \beta_{12} \log\left(\frac{y_{2,it}}{y_{1,it}}\right) \log\left(\frac{y_{3,it}}{y_{1,it}}\right) + \alpha_1 \log\left(x_{1,it}\right) + 0.5\alpha_{11}\left[\log\left(x_{1,it}\right)\right]^2$$
$$+ \sum_{p=2}^{3} \gamma_p \log\left(x_{1,it}\right) \log\left(\frac{y_{p,it}}{y_{1,it}}\right) + \theta_{xt} t \log\left(x_{1,it}\right) + \sum_{p=2}^{3} \theta_{ytp} t \log\left(\frac{y_{p,it}}{y_{1,it}}\right)$$
$$+ \delta_1 t + \delta_2 t^2 + v_{0i} + u_{0i} + v_{it} + u_{it}. \tag{10}$$

Equation (10) is estimated using the maximum simulated likelihood approach outlied in Badunenko and Kumbhakar (2017).

3 Data

The Flemish education system provides adult education in six vocational sectors: technology, management, environment, food, design, and metal and wood. To enrol, participants must be at least 18 years old. Although adult education is primarily meant for high school dropouts, individuals with a high school diploma are not precluded from participating. The completion of an adult education program leads to a formally recognised certificate that can be used on the labour market to secure a job. All adult education programs are privately organised and publicly funded. Adult education programs are grouped into five large adult education centres that are subsidised in an output-oriented manner by the Flemish government. These five centres are further divided into smaller centres present in different physical locations (21 cities) throughout Flanders. In general, each centre receives funding per participant who obtained an adult education certificate. However, the length of programs can vary considerably and lengthier programs receive more funding. Although the length of an adult education program varies as determined by the specific centre, most programs last about 1 year. There are no preset criteria for enrolment, although some adult education programs build on another programs. For these programs, completion of the previous program is required to proceed to the next one. The attendance of participants is not mandatory, but if participants do not sufficiently attend the classes, they are forbidden from participating in the exam. The programs are offered through modular education in which the subject material is subdivided into smaller components to reduce school dropout (Mazrekaj and De Witte 2020). Some programs are organised during the day, while other programs are organised in evening classes. Yet other programs offer a combination of both.

The data are compiled from SYNTRA Flanders, the public organisation that organises adult education in Flanders. We estimate inefficiency at the program level and cover the period 2006-2015. Our sample includes 120 programs observed over 10 years, totalling 1200 observations. Table 1 provides summary statistics for the outputs, inputs, and the determinants of both persistent and transient inefficiency. The outputs are based on the evaluation criteria set by the Flemish government, and several interviews conducted with adult education program directors (see Schiltz et al. 2019). The output variables represent (1) the average score on the final exam, (2) whether the learner was present during the classes as reported by the teacher, and (3) whether the

Table 1 Descriptive statistics

	Variable	Min	Mean	Median	SD	Max
y1	Average exam score	0.242	0.664	0.673	0.091	1
y2	Total presence in class	0.405	0.761	0.777	0.099	1
y3	Participation rate in exam	0.010	0.544	0.560	0.213	1
x	Cost per learner per session (euros)	0.635	9.097	7.648	8.365	110.468
z1	Gender balance	0.000	0.491	0.480	0.340	1
z2	Age of the learner	19.875	30.822	30.345	4.634	47.5
z3	Low educated (%)	0	0.101	0.088	0.089	0.667
z4	Sessions per program	0.693	3.832	3.761	0.990	7.366
z5	Learners per program	1.386	4.541	4.543	0.582	6.045
z6	Age of the teacher	29.365	46.448	46.648	6.124	72.795
z7	Teacher age composition	0	8.816	8.958	2.960	20.506
z8	Teacher hours composition	0	3.941	3.976	0.582	5.425
	Number of programs	1200				

learner participated in the exam. All outputs are measured as ratios, with a maximum value of 1. Summary statistics, provided in Table 1, suggest that 76% of the learners are present in class, whereas 54% participate in the exams. Although it may appear that these outputs are highly correlated at first sight, the correlation between each of the outputs does not exceed 0.33.

We consider a single available input (x), namely the cost per learner per session in euros. This input is calculated in two steps. First, we compute the total cost of a program by multiplying the average hourly wage of teachers assigned to the program and the total number of hours taught. Both are exogenous to the production process as they are set by the central government. In a second step, we divide the total cost of a program by the number of learners and the number of sessions to make it comparable across education centres. None of the components of x is chosen by the program and therefore input x can be treated as exogenous. As presented in Table 1, there are about 4 sessions and 5 learners per program. The cost per learner per session is, on average, 9 euro. However, some programs are considerably cheaper, whereas others are very expensive (up to 110 euro per session per learner).

Next, we include determinants of the transient inefficiency (variables z1 to z8). These determinants are in line with earlier studies that have estimated education production functions. The transient determinants include variables that change over time. First, we include gender balance of the program, given that previous studies have shown that girls-only schools typically enjoy a better average performance on the exams than mixed schools (Bradley et al. 2001). Gender balance is calculated as the ratio of boys over girls. The descriptive statistics in Table 1 suggest that about half of the student population in adult education is female. Then we include the share of low educated learners (learners who have finished high school at most) as a proxy for socioeconomic status (D'Inverno, Smet, and De Witte, In press). Furthermore, to explore potential scale economies, we control for the number of sessions and the

Table 2 Frequency of the program type

Type	Count
Design	230
Food	160
Management	210
Metal and wood	180
Environment	210
Technology	210
Total	1200

number of learners per program. As these determinants may have a nonlinear effect on inefficiency (Schiltz and De Witte 2017), we include them into the production function in logs. Whereas the number of sessions correlates with instruction time (Lavy 2015), the larger number of learners may reduce efficiency because the teacher time is spread more thinly (Bradley et al. 2001). Similarly, we include the average age of the teacher and the variation in teacher hours allocated to different teachers within a program to proxy for teacher experience and teacher commitment to the program (as in Cherchye et al. 2019). This may correlate with efficiency as inexperienced teachers may be less efficient (D'Inverno, Smet, and De Witte, In press). Given that adult education programs are primarily followed by high school dropouts who have decided to return to education, we include the age of the learner (on average 31 years) and we interact the share of low educated learners with age to investigate if the younger low educated participants are more motivated to achieve better academic results. Finally, we also add a time trend to investigate whether adult education programs are on average more efficient over time.

Finally, we allow persistent inefficiency to vary by the type of the program as the program types (e.g. food, management, design) might attract a different student population and have a different implication for the program efficiency. The persistent inefficiency determinants do not change over time.[4] We consider the six different types of programs as the determinants of persistent inefficiency in adult education. Table 2 provides the frequency of different programs.

4 Results

This section presents the results of the analysis. We first present the education production technology. Next, the persistent and transient inefficiency is analysed. A third

[4] It should be noted that the management can have a persistent and a transient component. Some styles of the manager may be specific to him/her (for instance ability), while the day-to-day style can be time-varying. The easiest way to think about the structural inefficiency is the one that is not easy to address in the short-run. For example, it is not easy to change the profile of the centre overnight. Hence, we believe that the type of centre is a good proxy for the hetereogeneity of structural inefficiencies. The transient or a short-term inefficiency on the other hand is easier to address as some short-term changes can bring efficiency improvements.

subsection discusses the determinants of the efficiency differentials, which provide insight into how efficiency can be enhanced.

4.1 Education production technology

To specify the education production function, we first estimate the most appropriate functional form. This important step is often ignored in the efficiency analyses, resulting in specification biases (Yatchew 1998; Schiltz and De Witte 2017). We compare the basic Cobb–Douglas specification against a more flexible translog specification. The Cobb–Douglas specification is rejected in favour of the translog. The LR statistic is 614.81, which is greater than the 1% critical value of the mixed Chi-squared with 9 degrees of freedom amounting to 20.97. As our output distance function is a full translog function in, technical change contains both neutral and non-neutral components. Technical change is neutral if coefficients at interaction terms of time trend and outputs and input are not significant. The hypothesis that $\theta_{xt} = \theta_{yt2} = \theta_{yt2} = 0$ is rejected, given that the LR test statistic 62.71 exceeds 10.5, the critical value of the mixed Chi-squared distribution at the 1 percentage level. Thus, the technological progress is non-neutral.

Having specified the production function, Table 3 presents estimates of the education production technology. The first thing to mention is that given our discussion that input is exogenous and that it can be shown that the ratios of outputs are exogenous, the estimation of the IDF does not suffer from the endogeneity issue. Further, to see if the results are robust to the choice of time period, we also estimate the model in which we exclude both the first and the last time periods (leaving 8 time periods instead of 10). The results of this exercise appear in the second column labelled 'restricted sample' of Table 3 (see also Table 5). If anything, the conclusions that we draw for the analysis based on the full sample can also be drawn from that of the restricted sample.

Given that the full translog specification includes interaction terms, the individual coefficients are not informative. Therefore, we present the summary statistics of the elasticities of ODF with respect to the input and the three outputs in Table 4. Theoretically, ODF is increasing in each output and decreasing in each input. The y2 and y3 elasticities are obtained from the estimation coefficients (Table 3) and the data, whereas the y1 elasticity is obtained using the homogeneity of degree 1 property of the ODF. Due to the duality (see Färe and Primont 1995), the said ODF elasticities are also the revenue elasticities. The ODF elasticity with respect to input x is negative for the majority observations, which is in accord with the ODF property. Still, the theoretical property is not satisfied for some observations. We also observe violations of the ODF properties for some observations when we consider ODF elasticity with respect to outputs.

4.2 Efficiency

Next, from the education production technology function, we can identify the programs that do not succeed in reaching the production frontiers. These programs have an efficiency shortfall, which might be due to persistent or transient reasons. The box

Table 3 Production technology

	Full sample	Restricted sample
Variable	Coefficient (SE)	Coefficient (SE)
	(1)	(2)
(Intercept)	0.180*** (0.018)	0.138*** (0.037)
log(y2/y1)	0.685*** (0.039)	0.769*** (0.049)
log(y3/y1)	– 0.039*** (0.014)	– 0.054*** (0.020)
log(x)	0.023** (0.012)	0.025* (0.014)
t	– 0.000 (0.006)	0.010 (0.012)
$\{\log(y2/y1)\}^2$	0.577*** (0.029)	0.574*** (0.037)
$\{\log(y2/y1)\}^2$	– 0.004 (0.003)	– 0.000 (0.005)
$\{\log(x)\}^2$	– 0.006** (0.003)	– 0.005*** (0.003)
t^2	– 0.000 (0.001)	– 0.001 (0.001)
log(y2/y1)*log(y3/y1)	– 0.032** (0.013)	– 0.023 (0.021)
log(y2/y1)*log(x)	– 0.119*** (0.016)	– 0.128*** (0.019)
log(y2/y1)*t	– 0.002 (0.004)	– 0.009*** (0.005)
log(y3/y1)*log(x)	0.011** (0.005)	0.013** (0.006)
log(y3/y1)*t	0.003*** (0.001)	0.004*** (0.002)
log(x)*t	0.001 (0.001)	0.001 (0.001)

Notes ***Significance at the 1% level; **Significance at the 5% level; *Significance at the 10% level

Table 4 Elasticity of output distance function

With respect to	1st Q.	Median	Mean	3rd Q.
x	– 0.0298	– 0.0173	– 0.0171	– 0.0037
y1	0.2736	0.3974	0.3953	0.5114
y2	0.4875	0.6075	0.6087	0.7371
y3	– 0.0133	– 0.0036	– 0.0040	0.0056

plots of efficiencies are shown in Fig. 1. For comparison purposes, the range on the vertical axis is the same for all efficiencies. The average overall efficiency of the programs amounts to 88.2%. This suggests a rather high overall efficiency level as the average program can only improve its outputs by 12%.

Further decomposing the efficiency, we observe that the overall inefficiency stems from the transient inefficiency. The mean transient efficiency level is 93.2% suggesting that adult education's managers can improve efficiency by about 7% if they would learn from best practice observations. However, the overall efficiency is also driven by persistent efficiency, which cannot be altered by the adult education programs. This source of efficiency amounts to 94.65% and is driven by the time-invariant differences between programs, stemming from, e.g. differences in difficulty level between the programs or differences in the cost structure of the programs. It is interesting to notice that for all types of efficiency we observe rather long tails. This suggests that despite the overall efficiency is rather high, some programs clearly lag behind.

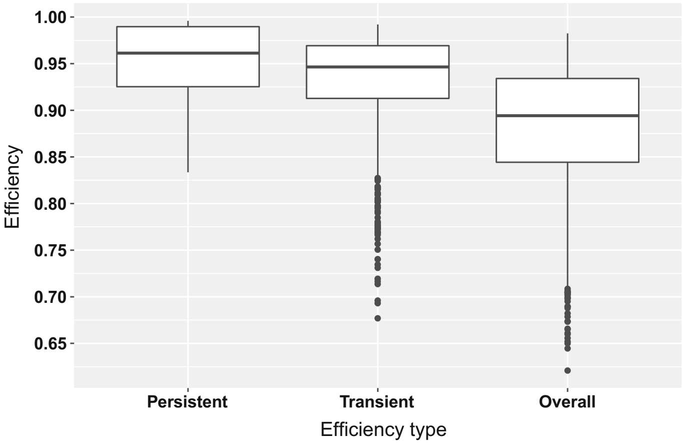

Fig. 1 Box plots of the persistent, transient, and overall efficiency. *Notes* The blue curves show the density of the age of the learner and the proportion of low educated. The most negative marginal effect is coloured blue, while the most positive is coloured red. A zero marginal effect is coloured white

4.3 Determinants of efficiency differentials

In the final step, we explain the differences in the efficiencies. This is a relevant step as it allows the adult education programs to open the black box and observe the underlying determinants of the (in)efficiency. The estimation results of the efficiency determinants are presented in Table 5. A positive coefficient suggests a larger σ_u^2 and, therefore, a larger inefficiency if the corresponding variable increases. By contrast, a negative coefficient implies that the factor is favourable for efficiency.

First, consider the determinants of persistent inefficiency. The results in Panel A of Table 5 suggest that the wood and metal program is the most efficient in the long-run. However, the difference with the other program types is rather small as only the design and management programs are statistically less efficient than the reference category. The observation that design and management are persistently less efficient is unexpected as particularly management programs should be able to succeed in acquiring significant scale economies (given that management programs can be taught in larger groups and with fewer resources). On the other hand, compared to the other types of adult education programs, it is likely that design and management programs attract a student population that is different from other programs in unobserved characteristics (e.g. motivation).

Panel B of Table 5 provides the determinants of persistent inefficiency. Except for the teacher's age and hours, all estimated coefficients are negative, suggesting that these variables are favourable for the efficiency. The coefficient of hours and age of the teacher is positive in the restricted same and negative in the full sample, however it is statistically insignificant. As the estimated coefficients only provide the direction of the effect, we also compute marginal effects. Table 6 presents summary statistics of elasticities of the transient inefficiency with respect to explanatory variables. The marginal effects suggest that more boys in the program have a significant favourable

Table 5 Estimates of the parameters of the error components

	Full sample	Restricted sample
Variable	Coefficient (SE)	Coefficient (SE)
PANEL A. Persistent inefficiency component, LHS variable is $\log \sigma^2_{u_{0i}}$		
(Intercept)	– 10.313*** (3.646)	– 10.044*** (3.504)
Type1 Design	6.200* (3.591)	5.970* (3.414)
Type2 Food	1.479 (3.900)	0.127 (4.834)
Type3 Management	6.842* (3.616)	6.643* (3.465)
Type4 Environment	5.348 (3.589)	5.103 (3.420)
Type5 Technology	5.525 (3.603)	5.304 (3.450)
PANEL B. Transient inefficiency component, LHS variable is $\log \sigma^2_{u_{it}}$		
(Intercept)	– 0.090 (0.825)	0.464 (1.029)
z1 (Gender balance)	– 0.333** (0.170)	– 0.421** (0.200)
z2 (Age of the learner)	– 0.038** (0.016)	– 0.056*** (0.020)
z3 (% low educated)	– 5.276 (3.825)	– 6.463 (4.900)
z4 (Sessions per program)	– 0.774*** (0.071)	– 0.881*** (0.097)
z5 (Learners per program)	– 0.155* (0.094)	– 0.143 (0.113)
z6 (Age of the teacher)	– 0.002 (0.009)	0.007 (0.011)
z7 (Teacher age composition)	0.045** (0.018)	0.064*** (0.021)
z8 (Teacher hours composition)	0.062 (0.100)	0.050 (0.119)
t	– 0.044* (0.026)	– 0.100*** (0.034)
z2*z3	0.132 (0.119)	0.191 (0.152)

Notes. *** Significance at the 1% level; ** Significance at the 5% level; * Significance at the 10% level

Table 6 Elasticities of the transient inefficiency

	Variable	Min	Mean	Median	Max
z1	Gender balance	– 0.166	– 0.082	– 0.080	0
z2	Age of the learner	– 0.895	– 0.378	– 0.388	1.080
z3	Low educated (%)	– 0.748	– 0.065	– 0.049	0.132
z4	Sessions per program	– 0.387	– 0.387	– 0.387	– 0.387
z5	Learners per program	– 0.077	– 0.077	– 0.077	– 0.077
z6	Age of the teacher	– 0.061	– 0.039	– 0.039	– 0.024
z7	Teacher age composition	0	0.200	0.203	0.464
z8	Teacher hours composition	0	0.030	0.030	0.031

influence on the efficiency scores. Also, more mature learners, as proxied by the age of the learners, have a significant favourable influence on the efficiency scores. For each year that the average age of the learners increases, the efficiency improves by 0.37 percentage points. We do not observe a significant correlation between being a low educated learner and transient inefficiency.

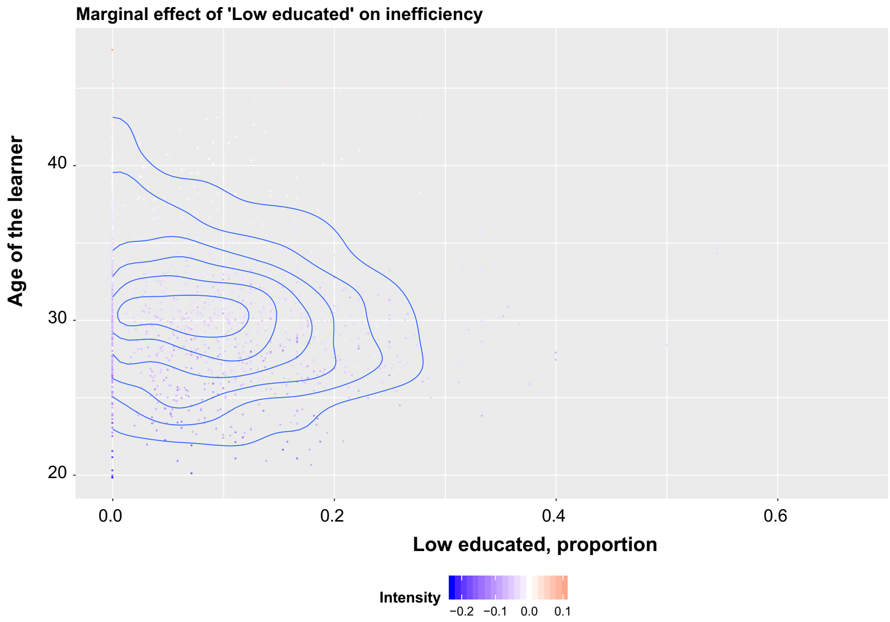

Fig. 2 Scatterplot of marginal effect of age of the learner and proportion of low educated on transient inefficiency

The next few variables deal with the program design and are fully at the discretion of the adult education program's management. First, we observe that having more sessions significantly increases efficiency. This result is in line with findings from instruction design that indicates that the social component of learning is relevant, particularly for adult education (e.g. Salomon and Perkins 1998). Also, a sufficient group size is needed. For each additional learner in the program, the efficiency score increases significantly by 0.07 percentage points. Exploring quadratic functions of this variable suggests that this relationship is linear. The age of the teacher seems to be irrelevant for the efficiency estimation, whereas the variation in teachers' age is unfavourable for efficiency. This is an interesting finding which should be further researched as traditional theories assume that diversity in teacher composition is favourable for the learning outcomes of students. The composition of teachers' workload does not seem to have a significant influence on the program efficiency, as does the mean interaction between the age of learners and the percentage of low educated learners. Analysing the latter more carefully, we observe that the interaction variable is favourable for transient efficiency, but only until the age of learners reaches 40 years. After that, its effect is negative. Figure 2 suggests that managers can reach larger efficiencies not only with younger learners, but when the proportion of low educated is smaller. This finding suggests that adult education might play a crucial role as a second chance education for young and highly educated people.

Table 7 IRF Estimates of the parameters of the error components

Variable	Coefficient (SE)
PANEL A. Persistent inefficiency component, LHS variable is $\log \sigma^2_{u_{0i}}$	
(Intercept)	– 2.676* (1.542)
Type1_Design	2.859** (1.422)
Type2_Food	0.977 (1.408)
Type3_Management	3.355** (1.483)
Type5_Environment	0.810 (1.465)
Type6_Technology	2.142 (1.381)
PANEL B. Transient inefficiency component, LHS variable is $\log \sigma^2_{u_{it}}$	
(Intercept)	– 7.774*** (2.193)
z1 (Gender balance)	– 0.779 (0.530)
z2 (Age of the learner)	– 0.073 (0.044)
z3 (% low educated)	12.950 (9.580)
z4 (Sessions per program)	0.771*** (0.145)
z5 (Learners per program)	1.083*** (0.295)
z6 (Age of the teacher)	– 0.038 (0.025)
z7 (Teacher age composition)	0.019 (0.048)
z8 (Teacher hours composition)	0.018*** (0.004)
t	0.028 (0.227)
z2*z3	– 0.519 (0.358)

4.4 Input requirement function

As mentioned before, the adult education centres are subsidised in an output-oriented manner by the Flemish government. Nevertheless, it is interesting to look at the input-saving side of the educational production process. Since there is only one variable input, we cannot specify a cost function. We have therefore estimated the Input Requirement Function (IRF), which is dual to the cost function for multiple inputs and which relates an input to outputs. The IRF treats x as an endogenous variable and outputs as exogenous. This is often preferred because outputs in service industries are exogenously given. To address this issue, we estimated the IRF with the same features as the ODF, except that the input variable (in log) appears as the dependent variable and the output variables (in log) are without ratios. Table 7 presents the coefficients of the determinants (heteroskedasticity function) of both inefficiency components. For brevity and to conserve space, we do not show the full set of coefficients of the input requirement function.[5]

The results for the long-run inefficiency are qualitatively similar to those of the output distance function. There are differences in the transient inefficiency component. The variables that define the structure of the program such as sessions per program and

[5] The table with all coefficients of the full translog input requirement function is available from authors upon request.

learners per program are associated with a larger transient inefficiency. The programs with a larger variety of hours composition are also less efficient. The determinants of the transient inefficiency for ODF are not relevant for the input-oriented side of centres' functioning.

5 Discussion

Compared to the only other available study on the efficiency in adult education (Schiltz et al. 2019), our estimate of inefficiency is rather high. Specifically, Schiltz et al. (2019) used a DEA model and found that adult education programs could improve their efficiency by 4% on average, whereas our estimate of inefficiency is 12%. Although we tackle the main issues in the previous literature in which inefficiency was estimated as a single component, it should be noted that this paper is also not without limitations. First, although we contribute to the literature by differentiating between persistent and transient inefficiency, we do not claim to present causal evidence. It is possible that unobserved factors not captured by our model are influencing our results. For instance, different vocational programs may attract student populations with different aspirations which may in turn influence the program outcomes. Future research could expand the range of control variables or use efficiency models in combination with causal inference methods. Second, from a methodological point of view, the distributional assumptions we made to estimate inefficiency with a stochastic frontier model may be viewed as restrictive. Third, although we considered three different outcomes, all the outcomes were educational. Future research may expand the range of outcomes to also include some labour market and social outcomes. Fourth, we solely considered a single input based on the teachers' wages. Although this represents the largest share of the total adult education costs, the costs of the material may also be important. Finally, it is unclear how the results from Flanders could be applied to other adult education systems. Further research should address these limitations.

6 Conclusion

This paper distinguished between the persistent and transient inefficiency of adult education programs using an advanced stochastic frontier analysis model on Flemishdata. We found that adult education programs could, given the available resources, improve their efficiency by 12% on average. About 5 percentage points of the inefficiency are persistent and difficult to tackle, whereas about 7 percentage points are at the discretion of the adult education management. We also investigated the determinants of inefficiency. The results indicate that social interaction is relevant as both more sessions and more learners per program increase efficiency. Moreover, adult education programs seem to be particularly useful for young low educated learners. Consequently, young people are especially likely to benefit from adult education programs after they have dropped out of high school.

Acknowledgements Deni Mazrekaj acknowledges funding by the Research Foundation Flanders (FWO) as Aspirant (Grant Number 1172519 N).

Compliance with Ethical Standards

Conflict of interest The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

References

Agasisti T, Gralka S (2019) The transient and persistent efficiency of Italian and german universities: a stochastic frontier analysis. Appl Econ 51(46):5012–5030

Badunenko O, Kumbhakar SC (2017) Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: do ownership, regulation and heterogeneity matter? Eur J Oper Res 260:789–803

Blanden J, Buscha F, Sturgis P, Urwin P (2012) Measuring the earnings returns to lifelong learning in the UK. Econ Edu Rev 31(4):501–514

Bradley S, Johnes G, Millington J (2001) The effect of competition on the efficiency of secondary schools in England. Eur J Oper Res 135(3):545–568

Cherchye L, De Witte K, Perelman S (2019) A unified productivity-performance approach applied to secondary schools. J Oper Res Soc 70(9):1522–1537

Colombi R, Kumbhakar SC, Martini G, Vittadini G (2014) Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. J Prod Anal 42:123–136

Commission E (2011) Tackling early school leaving: a key contribution to the Europe 2020 Agenda. European Commission, Brussels

D'Inverno G, Smet M, De Witte K, The effect of additional resources for schools with disadvantaged students: evidence from a conditional efficiency model. Europ J Oper Res (In Press)

De Witte K, López-Torres L (2017) Efficiency in education: a review of literature and a way forward. J Oper Res Soc 68(4):339–363

Färe R, Primont D (1995) Multi-output production and duality: theory and applications. Kluwer Academic Publishers, The Netherlands

Filippini M, Hunt LC (2016) Measuring persistent and transient energy efficiency in the US. Energy Efficient 9(3):663–675

Filippini M, Geissmann T, Greene WH (2018a) Persistent and transient cost efficiency—an application to the Swiss hydropower sector. J Prod Anal 49(1):65–77

Filippini M, Greene WH, Masiero G (2018b) Persistent and transient productive inefficiency in a regulated industry: electricity distribution in New Zealand. Energy Econ 69(1):325–334

Gralka S (2018) Persistent inefficiency in the higher education sector: evidence from Germany. Educ Econ 26(4):373–392

Hanushek EA (1986) The economics of schooling: production and efficiency in public schools. J Econ Literat 24(3):1141–1177

Hanushek EA, Woessmann L (2008) The role of cognitive skills in economic development. J Econ Literat 46(3):607–668
Heshmati A, Kumbhakar SC, Kim J (2018) Persistent and transient efficiency of international airlines. Europ J Transp Infrastruct Res 18(2):213–238
Kumbhakar SC (2013) Specification and estimation of multiple output technologies: a primal approach. Europ J Operat Res 231(2):465–473
Kumbhakar SC, Lien G, Hardaker BJ (2014) Technical efficiency in competing panel data models: a study of Norwegian grain farming. J Prod Anal 41:321–337
Lavy V (2015) Do differences in schools' instruction time explain international achievement gaps? Evidence from developed and developing countries. Econ J 125(588):F397–F424
Martin BC, McNally JJ, Kay MJ (2013) Examining the formation of human capital in entrepreneurship: a meta-analysis of entrepreneurship education outcomes. J Bus Ventur 28(2):211–224
Mazrekaj D, De Witte K (2020) The effect of modular education on school dropout. British Educ Res J 46(1):92–121
OECD (2019) Getting Skills Right: Engaging low-skilled adults in learning. Retrieved from www.oecd.org/employment/emp/engaging-low-skilled-adults-2019.pdf
OECD (2020) Secondary graduation rate (indicator). https://doi.org/.10.1787/b858e05b-en
Salas-Velasco M (2020) Assessing the performance of Spanish secondary education institutions: distinguishing between transient and persistent inefficiency, separated from heterogeneity. Manchester School 88(4):531–555
Salomon G, Perkins DN (1998) Chapter 1: individual and social aspects of learning. Rev Res Educ 23(1):1–24
Schiltz F, De Witte K (2017) Estimating scale economies and the optimal size of school districts. A flexible form approach. Br Edu Res J 43(6):1048–1067
Schiltz F, De Witte K, Mazrekaj D (2019) Managerial efficiency and efficiency differentials in adult education: a conditional and bias-corrected efficiency analysis. Annal Oper Res
Sneyers E, De Witte K (2017) The interaction between dropout, graduation rates and quality ratings in universities. J Oper Res Soc 68(4):416–430
Titus MA, Vamosiu A, McClure KR (2016) Are public master's institutions cost efficient? A stochastic frontier and spatial analysis. Res Higher Edu 58(5):469–496
Yatchew A (1998) Nonparametric regression techniques in economics. J Econ Literat 36(2):669–721

Affiliations

Oleg Badunenko[1] · Deni Mazrekaj[2,3] · Subal C. Kumbhakar[4,5] · Kristof De Witte[3,6]

✉ Oleg Badunenko
oleg.badunenko@brunel.ac.uk

Deni Mazrekaj
deni.mazrekaj@sociology.ox.ac.uk; deni.mazrekaj@kuleuven.be

Subal C. Kumbhakar
kkar@binghamton.edu; subal.c.kumbhakar@uis.no

Kristof De Witte
kristof.dewitte@kuleuven.be; k.dewitte@maastrichtuniversity.nl

1 Department of Economics and Finance, College of Business, Arts and Social Sciences, Brunel University London, Uxbridge UB8 3PH, UK

2 Department of Sociology, University of Oxford, Park End Street 42-43, Oxford OX1 1JD, UK

[3] Leuven Economics of Education Research (LEER), Naamsestraat 69, Louvain, KU 3000, Belgium

[4] Department of Economics, State University of New York, Binghamton, NY 13902-6000, USA

[5] Department of Innovation, Management and Marketing, University of Stavanger Business School, N-4036 Stavanger, Norway

[6] United Nations University – Maastricht Economic and Social Research Institute on Innovation and Technology (UNU-MERIT), Boschstraat 24, Maastricht 6211 AX, The Netherlands