LABOR USE EFFICIENCY OF ETHIOPIAN AIRPORTS

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ABSTRACT

This study analyses labor use efficiency of Ethiopian airports using an input requirement function approach. The study considers panel data for 13 international and domestic airports covering the period 2002-2017. The fixed effects, a multi-step model of separating persistent and transitory inefficiency, and maximum likelihood estimation techniques are used for estimating the airports' labor use efficiency. The study concluded that labor use and airport output were complementary hence expansion of airport facilities is recommended. Capital, energy, and maintenance and repair inputs substitute labor use. The efficiency results vary according to the models' underlying assumptions. The average labor use efficiency of the fixed-effects, multi-step and maximum likelihood methods are 47.52, 49.60 and 50.59% respectively. Despite these minor differences, many domestic airports performed relatively better compared to international airports. Thus, deployment of resources above the minimum requirements should be reconsidered as a source of cost reduction. The airports with high persistent inefficiency will continue to remain inefficient which may necessitate structural changes and revision of employment and labor use policies so as to increase their labor productivity.

KEYWORDS

labor use; productivity; persistent and transitory efficiency; airports; Ethiopia

1. INTRODUCTION

The Ethiopian economy has been growing rapidly since 2000. The main contributing factors in this are strong government interventions and policy direction towards mobilization of public resources for investments in infrastructure and human capital development (Shiferaw, 2017). According to Shiferaw Ethiopia is far behind many other low-income countries in terms of its human development index (HDI) ranking. Using the 2014 Human Development Report he shows that in Ethiopia the adult population years of schooling was 50% lower than the average for sub-Saharan Africa (SSA). Human capital resources play a significant role in agriculture, the manufacturing industry, and the service sectors including the air transport sector.

Apart from transporting passengers and freight, the air transport sector in general and airports in particular play a significant economic role as well. The sector contributes to the creation of employment, income generating capacity, and supporting the economy and its globalization. The aviation industry positively impacts global GDP in the form of direct, indirect, induced, and tourism effects (ATAG, 2018). As the economy of once country grow, the service sector including air transport demand increase and income generating capacity of the aviation industry also increase. Contribution and effect of the aviation industry also depends on the countries' level of economic and human resource development.

The main sources of revenue for the aviation sector are the service charges for transporting passengers and freight cargo. Airport Council International (2018) shows that the world's busiest airport was Hartsfield–Jackson Atlanta International Airport, Beijing Capital International Airport, and Dubai International. In contrast to the advanced world, aviation industries in African countries are relatively small. The busiest airports in Africa by number of passengers are the South African O.R. Tambo International Airport-Johannesburg, Cairo International Airport, and the South African Cape Town International Airport. Addis Ababa Bole International Airport – Ethiopia was the fourth busiest airport in Africa in 2017 (ACI, 2018). In general, airlines carried about 4.1 billion passengers worldwide and approximately 3.6% of the global GDP was supported by the aviation industry (ATAG, 2018).

The multidimensional contributions of the aviation sector are inducing attention to improving its quality and its provision of sustainable services. This is why there is an increasing demand to benchmark the airports and their efficiency measurement. There are two basic determinant factors of efficiency in airports' development: environmental factors and internal strategic decisions. Usually, the first one is beyond the management's control. The latter is a basic issue and concern of the airports besides that it is within the scope of the management. The main concern of research is on ways of minimizing the management's inefficiencies (Graham, 2005).

Decision-makers are seeking information about their airports' performance in relation to other similar airports. Graham (2005) explains that there is no consensus among airports as to what the best management tools are. In the recent period, airports have been focusing on more business and following commercially oriented approaches. Similarly, many airports in the advanced world have been privatized; motivated by better and more efficient management.) During the last three decades Ulku (2009) argue that the focus of many airports has been on business and commercially oriented approaches while others have been working with scholars to investigate how to improve the management of the airports.

According to Ulku (2009), the increasing level of competitiveness basically assists airports to survive, gain more market share and market power. Moreover, airports have various strategies in relation to their level of development. Hence, there is an increasing trend of coping with and using existing resources effectively as frontline solutions. In this regard, Kazda and Hromádka (2011) suggest focus on trend in effective utilization of existing resources. Similarly, terminal building resources should be designed for shortest passenger queues. The frequently observed challenges in many airports are optimization problems that arise at the operational planning and at the integration of system control levels (Kazda and Hromádka, 2011).

The main drawback for promoting airports' efficiency are the challenges of limited hours of operations, interruptions in system integration, and workforce coordination that have been creating congestion at the Addis Ababa Bole International Airport hub. Consequently, the delays have an impact on other domestic airports. This leads to inconvenience for customer airlines and passengers which could have serious implications for airlines smooth connections from their hub. When such problems occur repeatedly it impacts the airport's market share and market power. For addressing these problems, there is a need for using more manpower and resources for supporting airport operations. Hence, additional resources should help to increase the operational, technical, and allocative efficiency of airports through a reduction in idle hours.

It is a fact that the aviation industry is a networking transport system throughout the world and Ethiopia is a part of it. Despite positive and negative global influences, Ethiopian airport services continue to face inconsistency in delivering quality service, low equipment productivity, and capacity constraints in addressing the fast-growing Ethiopian airlines that require additional equipment and manpower productivity. The current practice of the use of airport facilities is limited to morning and evening flight operations. This implies capital productivity per hour are low. Besides, there is the problem of system integration, skills, experience and coordination of the workforce during operations. Skytrax cutomer review report (2019) showed that Addis Ababa Bole international airport service delivery is far below the required level of customer satisfaction.

In empirical literature, labor productivity has been paid extensive attention, though labor use efficiency is not well addressed (Hjalmarsson and Veiderpass, 1992). The need for and importance of measuring labor use efficiency is unquestionable. Hence, the objective of this research is to examine the labor use efficiency, separating time-invariant (persistent) and time-varying (transitory) labor use efficiency of Ethiopian airports. Three models are estimated: the fixed-effects time-invariant model suggested by Schmidt and Sickles (1984), the Kumbhakar and Heshmati (1995) model, and the MLE time-variant efficiency model. The models cover a whole range of aspects of efficiency, its estimation and a sensitivity analysis of the results. In addition to benchmarking, this will also help Ethiopian airports to compare and contrast their labor use efficiency. Moreover, this study will also help to drive important policy measures that follow from its findings. More importantly, previous empirical research on labor use efficiency was limited so this research makes a significant contribution to labor use efficiency literature and its application to the airport sector.

The rest of this research is organized as follows. Section 2 reviews literature, and the data and methodology are described in Section 3. Section 4 gives the methodological framework of the study. The model's specifications of the panel data input requirement function are given in Section 5. The model's estimation and a discussion of the results are given in Section 6. Section 7 gives the conclusion and based on the findings makes some recommendations.

2. LITERATURE REVIEW

This literature review focuses on productivity related empirical application of labor use and labor productivity. Among the many studies those on labor use efficiency in the service sector and manufacturing industry have been reviewed.

The concept of technical efficiency was derived from the technical change concept which was first developed by Solow (1957) and called the residual of production activities. Solow also made three assumptions when measuring technical change: constant returns to scale, Hicks-neutral technical change, and perfect competition. In addition, the modeling production function has an important role in analyzing returns to scale, technical changes, and growth in rate of total factor productivity. Productive capacity in a broad context is an integrated outcome of existing and potential resources, accumulation of human capital, setup of institutions, as well as requiring nurturing entrepreneurs' skills and fostering innovations.

In labor use efficiency literature, pioneering work is by Kumbhakar and Hjalmarsson (1995) for the Swedish social insurance office which considers the frontier production function based on a multi-stage panel data model approach. These authors estimated the parameters of a flexible input requirement and decompose inefficiency into time-invariant, time-varying and residual components. Their empirical results show the existence of substantial variations in labor use efficiency among the social insurance offices. Mean efficiency declined over time and there was the presence of economies of scale, implying that most of the offices were found suboptimal in size for labor use.

Battese et al. (2000), studied the deregulation impact and banking crisis related consequences on productivity and productivity growth in the Swedish banking industry using the translog stochastic frontier panel data model. They also define the labor use frontier in the same way as the frontier model proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) to account for the random and inefficiency effects. Battese et al. (2000) found that inefficiency of labor use in Swedish banks was significant. They also found that different types of banks, number of branches, total inventories, and year of observation significantly affected the banks' labor use inefficiency.

Labor use efficiency has also been studied in Tunisian manufacturing industries (Haouas et al., 2003). These authors addressed the model of dynamic employment demand with the flexible adjustment parameter and measured labor use employment efficiency among six Tunisian manufacturing sectors over 25 years. The adjustment process was at the industry level and time specific. These authors found that long-run employment demands were highly responsive to output changes, capital stocks and wages. Besides, large variations were observed in the speed of adjustment for employment as well as degree of labor use among industries and over time. During the liberalization period labor markets were more flexible and employers could adjust faster than they could in the regulated system.

Bhandari and Heshmati (2005) estimated dynamic labor demand using a flexible adjustment approach. Labor use and its adjustment in Indian manufacturing showed evidence of considerable dynamism in adjusting its workforce. Their findings showed that in India long-run labor demands were most responsive to output, followed by capital and wages. They also observed that Indian manufacturing was not inefficient in labor use since the speed of adjustment to employment size was closer to the optimal level.

Swedish saving banks' labor demand and efficiency was analyzed by Heshmati (2001). He applied the flexible translog functional form where demand for labor was a function of wages, outputs, quasi-inputs, and a time variable using the panel data model. In terms of labor demand, output elasticity was positive and wage elasticity was negative implying that labor demand was responsive to changes in both outputs and wages. The result showed that the sample banks were technically 96% efficient in labor use.

Loizides and Tsionas (2002) explain total factor productivity (TFP) measurement and a growing econometric interest in it during the past four/five decades. In particular, TFP has been used for making comparisons across countries and across time. Their model was developed using general indices of technical change and applied to firm level panel data. It is reasonable to assume a model's specifications in the transport sector as producing two types of outputs: passenger and freight transportation. In most cases, the capital factor input is fixed while maintenance and repairing is considered a variable input. Other factors of production are labor, energy and wage and price of energy. In contemporary globalization, airport infrastructure is categorized as major infrastructure as compared to other infrastructure. Besides, efficiency is a major issue in airports' management, though predominantly the public ownership nature of the airports makes them susceptible to and prone to inefficiency behavior (Barros, 2008).

The concept of inefficiency has remained the same since its inception. According to Farrell (1957) inefficiency is the failure to produce the maximum possible output for given inputs. Couto and Graham (2009) add that allocative inefficiency occurs as a result of wrong or sub-optimal choice of input proportions given their prices. Existence of both inefficiency types increases the total cost of production or services. Labor productivity, on the other hand, has been defined by Heshmati and Rashidghalam (2018) as a firm's ability to generate maximum production. In their study on Kenya's manufacturing abor productivity and its determinants, they found that capital intensity and wages significantly and positively affected labor productivity. They also found that better training and higher education yielded better labor productivity. Heshmati and Kim (2016) and Heshmati et al. (2018) analyzed performance of 39 international airlines for the period 1998–2012 using stochastic frontier analysis. They find significant variations in airlines efficiency and its changes in over time.

Haouas and Yagoubi (2004) explained that an extensive use of human capital was inefficient compared to partially used technical infrastructure and they found that less efficient industries were expected to adjust faster than the efficient ones. This means that industries closest to the labor requirement frontier have a lower speed of adjustment after liberalization as compared to industries that are further away from the frontier. Haouas et al. (2003) define labor use efficiency as the ratio of actual to optimal employment meaning that those having a ratio greater than one are over-using labor for a given level of output.

Regarding complementarity and substitutability of labor with other factors such as capital, energy, maintenance and repairing, Lachmann (1947) found that factor input variables complemented a production plan and played a role in the production process. While he saw substitution as a phenomenon of changing needs arose when the existing plan went wrong. Both have their own importance and Lachmann underlined that substitutability focused on the same output with a different combination of factors while complementarity depended on the 'technical rigidity' in changing the output than in the factor of production.

Sectoral differences in the degree of capital-labor substitutability have also been analyzed by Mućk (2017) who found that sectors having higher elasticity of substitution between capital and labor enjoyed more advantages of changing. In other words, when the wage to rental rate ratio changed, the more flexible the sector the better as compared to being less flexible. Mućk concluded that capital-labor ratios were the driving force in structural changes as they saw structural changes push out United States from the agriculture sector. Sector level structural changes can also be applied to the air transport sector through introducing advanced new technologies which contribute to capital, energy, and increased maintenance and repairing and as a consequence the share of productive labor shrinking to a certain level.

3. DATA AND DESCRIPTION OF THE VARIABLES

This study uses a balanced panel data of 13 Ethiopian airports covering the period of 16 years (2002-2017) with 208 observations. Geographically all the 13 domestic and international airports are distributed throughout the country. The finance related data is extracted from their final annual external audit reports, whereas human resource data systems are the main data source for labor force and working hours. Passenger and freight cargo data is collected from the statistics departments of Ethiopian airports.

The dependent variable is measured by the total employment (L) of each airport in effective working hours excluding weekends, annual leave, and holidays. The model's independent variables are average wage (W), passengers (Yp) and freight cargo (Yc) transported as aggregate output per year (Y), capital investments (K) energy use (E) and maintenance and repairing services (M) are measured in per effective labor hour.

Airport services have a multi-output and multi-input nature. Literature refers to the number of passengers transported, air traffic movements, and cargo transported in kg as the aviation industry's output variables. This research uses passengers transported (Yp) and freight cargo (Yc) as outputs produced by the airports. Revenue generation is the core business of the airports. The most prominent means of generating revenue are related to airports' outputs like aircraft movements (Ya), passenger movements, and freight cargo transportation. Airports collect reasonable service charges when an aircraft uses the runway, taxiway, apron, and aircraft support from ground handling activities. Besides, a significant amount of revenue is also collected from non-aeronautical activities such as duty-free shops, food and beverage outlets, special lounges, parking services, and others.

Airports have different types of fixed and variable inputs. Almost all capital inputs (K) are categorized as fixed, for example, the number of passenger terminal buildings with various facilities and equipment such as check-in counters, baggage handling systems, number of boarding gates, and passenger boarding bridges. Aircraft movement areas such as the number of runways, taxiways, and the apron area are also considered capital inputs. The rest of the capital are sub-stations or power houses with standby generators including electrical and system networking.

Aircraft and passenger movements at airports are managed by a qualified and experienced workforce. When an aircraft lands and takes off, the runway lighting, taxiway, and guidance in the apron area require expertise. Besides in all terminal building there are passenger customer handlers. An interrupted energy input measured in terms of lighting and fuel consumption is very critical for all airports. Communication between the terminal, tower, and aircraft can only be smooth if there is an uninterrupted power connection between and among all systems, facilities, and airport equipment including fire trucks.

In addition to the terminal building, runway/taxiway, and the apron area's maintenance and repairing, facilities such as lifts, escalators, powerhouse, data room, data centers, and the entire system and networking need regular maintenance and repairing services. In this research, the labor use frontier is specified for one aggregate output and three inputs. Important inputs and outputs are described in Table 1. Monetary variables are in fixed 2009 prices.

Table.1. Summary statistics of the data (2002-2017), (NT= 208 observations)

Variable	Definitions	Mean	Std. Dev.	Min.	Max.	CV
L	Man-day hours of effective labor	96,188	139,751	5,040	756,000	1.45
Yp	Annual passenger movements in 1,000 kg	40,900	143,000	120	1,020,000	3.49
Yc	Air freight cargo transported per year in 1,000 kg	11,400	40,400	0.001	243,000	3.53

Y	Aggregate passengers and freight cargo outputs in 1,000 kilogram	52,300.	178,000	120.691	1,260,000	3.40
Ya	Annual aircraft movements	6,891	16,624	222	111,202	2.41
K	Capital investments per effective labor hour	3,285	4,791	65	30,163	1.43
M	Maintenance and repairing expense per effective labor hour	19.93	25.22	0.12	165.85	1.27
W	Average wage per year	47,580	18,440	2,715	14,8704	0.39
E	Energy per effective labor hour	3.64	2.25	0.71	12.57	0.62

Source: Authors' calculations using data from Ethiopian Airports.

In this study man-day effective labor hours (L) is the dependent variable while annual passenger movements converted into kg equivalent (Yp) and annual air freight cargo transported in kg (Yc) are the output variables. Capital investments per effective labor (K), average wages (W), and energy consumption (E) per effective labor hour are inputs or explanatory variables. Other variables such as maintenance and repairing expenses per effective labor (M) and annual aircraft movements (Ya) are additional explanatory variables. Since their estimation results were not statistically significant, the study excludes them from the analysis but yet due to their importance are reported in Table 1.

The output value of passengers converted into weight was on average 40.9 million kg and the cargo freight 11.4 million kg. When comparing airports, the smallest airport transported 119,700 kg passengers and had a zero cargo share while the biggest airport reached more than 1 trillion kg equivalent of passenger and 243 million kg of freight cargo. A statistical analysis of the passengers, hours of labor, aircraft movements, and kg of freight cargo including average wages per year have very high range of variations. Similarly, the value of the standard deviation is very high compared to the mean values. This shows the existence of extreme variations between airports and significant growth within airports over the study period.

The coefficient of variation (CV) defined as the ratio of standard deviation to the mean of the variables is higher in passenger movements and freight cargo transported indicate large dispersion around the mean, and high capacity and utilization differences among airports. On the other hand, average wages and energy per labor hour (0.62) had lower CV values.

The mean wage per worker was 47,580 Birr per annum with a standard deviation of 18,440 Birr showing significant variability among airports as well as among employees. Similarly, the mean of capital investments per effective labor hour was about 3,284 Birr with a minimum value of 65 and a maximum value of 30,161 Birr. This indicates extreme variability and is proved by a standard deviation of 4,791 Birr per year. Lastly, the mean effective labor hour (L) was 96,188 hours. The minimum effective labor hours per airport were 5,040 while the maximum effective working hours per airport were 756,000. Such extreme variability is attributed to large variations in aircraft and passenger movements in the respective airports.

Two issues worth mention are extension of the data period and exchange rate. Regarding the dollar to Ethiopian Birr exchange, in Ethiopia capital investment is valued in ETB, the dollar to the ETB exchange rate is highly volatile and unpredictable. Hence the extreme fluctuation is not reflected in employee salary though consumer consumption is adversely affected.

Estimation results were extremely unpredictable and totally unrealistic. The author prefers to focus on the real value and average value of ETB.

The study data covered the period of 2002 up to 2017. Additional data cannot be found due to the merge of Ethiopian airlines and Ethiopian airports to create the Ethiopian airlines' group. As a result of this major policy change, statistical data management has totally changed. Besides new manpower deploying, and reshuffling has been conducted. Hence, it is not an easy task to find additional data, as well as the introduction of new management, need a separate efficiency analysis.

4. THE EMPIRICAL LABOR REQUIREMENT FRONTIER MODEL

This section presents the stages involved in developing the frontier input requirement functions. Production is a process that represents a transformation of inputs into outputs (Kumbhakar and Wang, 2010). Assuming single output (Y) and multi-inputs (X) the production function can be given as:

(1) $Y = f(X, t)$

where the function $f(.)$ is governing the input-output relationship and t represents technology. Assuming that a production possibility frontier (PPF) has two outputs and multi-inputs, Kumbhakar and Hjalmarsson (1998) formulated the PPF model as:

(2) $f(X_J, t, Y_m) = 0$

where X and Y are vectors of inputs and outputs, t represening technology, and other inputs may be specified depending on the technology requirements.

The labor input requirement function is defined as the relationship that minimizes use of labor with a given amount of output and technology. Kumbhakar and Hjalmarsson (1995) describe the general framework of labor use production function as:

(3) $L = f(X, Y, t)$

It defines the labour requirement function for production of a given level of outputs produced using the labor and other inputs. The most common inputs other than labor are capital, energy, materials, and technology.

As explained by Rashidghalam et al. (2016) the stochastic frontier model is directly related to the objective of input minimization for a given output. Once the PPF satisfies the regulatory conditions referred to in Diewert's (1974) work, the average labor requirement function is specified as:

(4) $L = f(X, Y, t)\exp(v)$

where v is the random error term. We can also rewrite the model incorporating the inefficiency components (u_i) as:

(5) $L = f(X, Y, t)\exp(v + u)$

Here the term $u \geq 0$ indicates a firm's inefficiency and v represents the statistical noise that can take both positive and negative values. Inefficiency is measured relative to firms' operating on the frontier obtained by setting $u = 0$.

Battese et al. (2000) investigated the labor use translog frontier model in the Swedish banking industry. In this model, the total labor hours used per year was the dependent variable while total public loans, maximum guarantees, deposits, number of branches, value of inventories, and year of observations were considered in the analysis. The v_{it} random error was assumed to be independent and identically distributed with $N(0, \sigma_v^2)$.

Assuming an industry is using more labor than minimum for producing a given level of output. According to Haouas et al. (2003) such an assumption is possible any time. It can happen due to variations in demand, performance level, degree of capacity utilization, and market conditions. Despite this, firms operate with the objective of minimizing labor inputs. There is a labor requirement frontier which is a potential target for any rational labor minimizing firm.

Let the minimum target level of labor be denoted by L_0^* and the actual level by *L* used in production of output *Y*. Here two possible scenarios are worth mentioning. The first one is if $L > L_0^*$, indicating an overuse of labor which is clearly an indication of employment inefficiency. The second concern is if $L = L_0^*$, indicating labor is used efficiently and the actual labor employment is close to the labor requirement frontier.

Estimating labor use efficiency is done assuming a parametric functional form $f(x)$. First the frontier function is estimated and then the degree of inefficiency. According to Kumbhakar and Wang (2010) the various methods of estimation and the choice of method depend on whether distributional assumptions of the error components are preferred, or it is assumed without any distributional assumption. The third approach is using very specific distributional assumptions of the error components and applying the maximum likelihood method. Besides, there are a number of approaches that lie between these two extremes. This study focuses on the maximum likelihood method with a distribution free approach.

5. LABOR USE MODEL'S SPECIFICATION AND ESTIMATION

Assume that the effective labor requirement function of Ethiopian airports can be represented as in Equation (5). The inverted factor demand or labor use is specified as a function of wage, different services produced, capital intensity, energy, material use, and technology. Diewert (1974) was the first to introduce the inverted factor demand function. The log linear labor requirement function is written as:

(6) $\ln L_{it} = \alpha_0 + \beta_1 \ln W_{it} + \beta_2 \ln Y_{it} + \beta_3 \ln K_{it} + \beta_4 \ln E_{it} + \beta_t t + \varepsilon_{it}$, i = 1, 2, 3, …, N

where i represents the i^th^ airport unit, t the t^th^ time period, $\ln L_{it}$ is log of effective labor hours, $\ln W_{it}$ is log of average real wages, $\ln Y_{it}$ is log of aggregate output of passenger and freight cargo, $\ln K_{it}$ is log of capital per effective labor hour, $\ln E_{it}$ is log of energy consumption per effective labor hour, and ε_{it} is the error term. Capital is represented by the values of the fixed assets. Each airport's energy consumption is the sum of its total fuel and electicity consumption. The error term is decomposed into statistical noise (v_{it}) and inefficiency (u_{it}) components.

Various models have been developed based on different assumptions of inefficacy. This study uses three models: the fixed-effects model, KH-1995 model, and the MLE approach.

Model 1: Time-invariant fixed-effects model

In this model estimation can be done without distributional assumptions. According to Schmidt and Sickles (1984) the time-invariant fixed-effects stochastic frontier model is similar to the standard FE panel data. They applied the standard estimation method for estimating the parameter of the model. According to Parmeter and Kumbhakar (2014) the standard FE model can provide consistent estimates of β , though $\hat{\alpha}_i$ is a biased estimator of u_i. By construction, $u_i > 0$ and the individual effect α_i is treated as fixed and unobserved individual effects.

In the FE approach, u_i is allowed to be correlated with x_{it}. According to Mundlak (1961) heterogeneity is believed to be correlated with the inputs under consideration. This is one of the desirable properties of the empirical applications of the model. In contrast, the FE approach excludes other time-invariant regressors to avoid collinearity with α_i (Kumbhakar et al., 2015; Parmeter and Kumbhakar, 2014). Thus, the least squares estimation of the FE model includes individual dummies as a regressor for α_i which we call the least square dummy variable (LSDV) method.

According to Kumbhakar et al. (2014, 2015), and Parmeter and Kumbhakar (2014) different approaches can be followed to removing α_i which is unobserved individual effects. As a result, if applying the first difference, the within transformation can easily eliminate α_i. Hence, the transformed model can be estimated using OLS and the OLS estimator of $\hat{\beta}$ is a consistent estimator from which the values of $\hat{\alpha}_i$ have been recovered. Again $\hat{\alpha}_i$ is obtained using a simple transformation to recover $\hat{u}_i > 0$ that will also be a consistent estimator if $T \to \infty$. Kumbhakar et al. (2017) and Parmeter and Kumbhakar (2014) elaborate on the time-invariant model in which consistent estimates of β can be obtained through the transformed model as $T \to \infty$. Thus, $\hat{u}_i$ is estimated based on Schmidt and Sickles' (1984) model as:

(7) $\hat{u}_i = \hat{\alpha}_i - \min_i \{\hat{\alpha}_i\} \geq 0$, i = 1, 2, 3, …., N

The most efficient unit in the sample is considered to be 100% efficient while the inefficiency estimates in the fixed-effects model are relative to the best unit in the sample. The model is very sensitive to outlier observations forming the frontier reference unit and the inefficiency and heterogeneity effects are confounded. Firm-specific efficiency is obtained from:

(8) $\hat{TE}_i = \exp(-\hat{u}_i)$, i = 1, 2, 3, …, N

As stated by Rashidghalam et al. (2016) a limitation of the FE model is the assumption of time-invariant inefficiency. In the FE model, individual heterogeneity and inefficiency are not separated. The core idea of this model is that inefficiency levels do not change over time though it may vary across individuals. According to Parmeter and Kumbhakar (2014) and Kumbhakar et al. (2015) the inefficient unit in the FE never change over time which means that firms do not learn over time. Thus, these inefficiency conditions may be related to the managerial capabilities of the firms. Market competition is so dynamic that such restrictive are unrealistic.

Model 2: Time-variant model separating persistent and transitory inefficiency

The distinction between persistent (time-invariant) and transitory (time-varying) components of inefficiency were improved simultaneously following Colombi et al. (2014) and Kumbhakar et al. (2014). The underpinning concept is that time-invariant inefficiency is considered as persistent inefficiency which is part of the management style of firms and such inefficiency cannot be resolved without changes in the industry policy. However, despite these facts, the residual component of inefficiency might change over time with the existing management system and without a change in a firm's operations (Kumbhakar and Heshmati, 1995; and Kumbhakar et al., 2014).

Here the labor use efficiency follows Kumbhakar and Heshmati (1995) model including its separation procedure for persistent and transitory efficiency componnets which is specified as:

(9) $\ln L_{it} = \alpha_0 + f(W_{rt}, Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + v_{it} + (u_i + \tau_{it})$

where the error term ε_{it} is decomposed into $\varepsilon_{it} = v_{it} + u_{it}$, where u_{it} is inefficiency and v_{it} is the statistical noise. Next is decomposing inefficiency into persistent (u_i) and residual transitory inefficacy (τ_{it}), that is, $u_{it} = u_i + \tau_{it}$. The first component is firm-specific while the second is both firm- and time-specific. To estimate the model let us rewrite Equation (9) as:

(10) $\ln L_{it} = \alpha_0 + u_i + f(W_{rt}, Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + v_{it} + (\tau_{it} - E(\tau_{it}))$

$$\ln L_{it} = \alpha_i + f(W_{rt}, Y_{nt}, K_{rt}, M_{it;} E_{rt}; \beta) + w_{it}$$

Hence, w_{it} has zero mean and constant variance. Equation (10) fits the standard panel data model with firm-specific effects, and it can be estimated either by fixed-effects or the random-effects frameworks. The estimation procedure under the fixed-effects model is a multi-step framework which involves several steps:

Step 1: The standard within transformation is conducted to remove α_i. Then the within transformed w_{it} will generate a random variable that has zero mean and constant variance. After this OLS can be used on the within transformed data to obtain a consistent estimate of β.

Step 2: Estimating u_i based on the minimization of $\hat{u}_i = [\min_i (\hat{\alpha}_i] + \hat{\alpha}_i = \bar{r}_i - \min \bar{r}$, where $\hat{\alpha}_i$ is the i[th] fixed effect. The inefficiency u_i is estimated relative to the best unit in the sample.

Step 3: Once we have obtained β and u_i, we can calculate the residual $e_{it} = y_{it} - x'_{it}\hat{\beta} + u_i$. Here an additional assumption of maximum likelihood can be used to separate v_{it} from τ_{it}.

Step 4: Having removed $\hat{\beta}_0$ from e_{it}, a JLMS conditional mean or mode technique can be used for estimating τ_{it}.

Model 3: Maximum Likelihood Estimation method

By imposing distributional assumption, the model can be estimated by maximum likelihood method. The model and its error components can be written as:

$$\begin{aligned} &\ln L_{it} = f(W_{it}, Y_{it}, K_{IT}, E_{IT}, M_{it}; \beta) + \varepsilon_{it} \\ (11)\quad &\varepsilon_{it} = v_{it} + u_{it} \\ &v_{it} \sim N(0, \sigma_v^2) \\ &u_{it} \sim N^+(0, \sigma_u^2) \end{aligned}$$

Kumbhakar et al. (2015), Filippini and Greene (2016), and Rashidghalam et al. (2016) note that the accuracy of the procedure enables the ML estimation method to generate higher efficiency in its estimation at the cost of strong distributional assumptions. Accordingly, the likelihood function for the ith observation is written as:

(12) $\ln L_k = cons + \ln \Phi(\frac{\mu_{k^*}}{\sigma_*}) + \frac{1}{2}\left\{ \frac{\sum_t \varepsilon_{it}^2}{\sigma_v^2} + \left(\frac{\mu}{\sigma_u}\right)^2 - \left(\frac{\mu_{i^*}}{\sigma_u}\right)^2 \right\} - T\ln(\sigma_v) - \ln(\sigma_u) - \ln\Phi\left(\frac{\mu}{\sigma_u}\right)$

where $\mu_{i^*} = \frac{\mu\sigma_v^2 + \sigma_u^2 \sum_t \varepsilon_{it}}{\sigma_v^2 + T\sigma_u^2}$ and $\sigma_* = \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + T\sigma_u^2}$

The model with four error component structure is written as:

(13) $\ln L_{it} = \alpha_0 + f(W_{rt}, Y_{nt}, K_{rt}, E_{rt}; \beta) + \mu_i + v_{it} + \eta_i + u_{it}$

Hence, $\eta_i > 0$ and $u_{it} > 0$ are the two inefficiency (time-invariant and time-varying) and μ_i and v_{it} are the other two firm heterogeneity effects and random errors respectively. In this model Kumbhakar et al. (2014) and Heshmati et al. (2016) explain the key multi-step procedure and rearrange Equation (9) as:

(14) $\ln L_{it} = \alpha_0^* + f(W_{rt}, Y_{nt}, K_{rt}, E_{rt}; \beta) + \alpha_t + \varepsilon_{it}$

where $\alpha_0^* = \alpha_0 - E(\eta) - E(u_{it})$; $\alpha_i = \mu - \eta_i + E(\eta)$ and $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$

The general error term ε_{it} is decomposed into $\varepsilon_{it} = v_{it} + u_{it}$, where u_{it} is inefficiency and v_{it} is statistical noise.

The unknown parameters are estimated by maximizing the log-likelihood function (Greene, 2008; Filippini and Greene, 2016; Colombi et al., 2011; and Kumbhakar et al., 2013). Once the parameter of the model is estimated, inefficiency of each i can be computed from either the mean or the mode based on Kumbhakar et al.'s (2015) estimation approach.

Similarly, the α_i and ε_{it} have zero mean and constant variance. As a result, Equation (14) can be estimated in three steps: The first step estimates $\hat{\beta}$ by using the MLE approach. This model gives the predicted values of $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$. The second step follows time-varying inefficiency u_{it} of first step that estimated using the predicted values of $\hat{\varepsilon}_{it}$. The model specification in the second step is:

(15) $\varepsilon_{it} = v_{it} + u_{it} + E(u_{it})$

where v_{it} is assumed to be i.i.d. $N^+[0, \sigma_v^2]$ and u_{it} is assumed to be i.i.d. $N^+[\mu, \sigma_u^2]$ that produces $E(u_{it}) = \sqrt{(2/\pi)}\sigma_u$. Equation (14) can be estimated using the standard SF technique. Kumbhakar et al. (2015) referred to Battese and Coelli (1995) and Jondrow et al. (1982) model and this process produce the prediction of time-varying residual inefficiency component u_{it} by using $\exp(-u_{it}/\varepsilon_{it})$. In the final step, Equation (13) is estimated in terms of η_i following a similar procedure as in step two and applying the best linear predictor of α_i from step one:

(16) $\alpha_i = \mu_i - \eta_i + E(\eta_i)$

Thus, μ_{it} is assuming i.i.d. $N^+[0, \sigma_\mu^2]$ and η_i is i.i.d. $N^+[0, \sigma_\eta^2]$ produces $E(\eta_{it}) = \sqrt{(2/\pi)}\sigma_\eta$. We can estimate persistent efficiency from $PTE = \exp(\eta_i)$; hence, the overall efficiency (OTE), is found from the product of PTE and RTE, that is, *OTE=PTExRTE*..

6. DISCUSSION OF THE RESULTS

The econometric model's specification and selection show that the translog functional form for a labor use efficiency analysis was not applicable. Thus, the study focused on the Cobb-Douglas labor use function. This model was also tested for the suitability of all the basic assumptions of the stochastic frontier model. The next step was determining the selection of the fixed-effects versus random-effects model for which the Hausman test was conducted. The null hypothesis of no systematic difference was rejected in favor of the fixed-effects model. Thus, the fixed-effects model of time-invariant and time-varying labor use inefficiency was the preferred model. In addition to the fixed-effects model, maximum likelihood estimation method and multi-step estimation approach of the inefficiency effect were also applied to increase the efficiency of the estimation process. In this study by assuming a fixed-effects procedure it was able to control for unobserved airport specific heterogeneity. Including time trend, we further control for unobserved time effects.

In contrast to the time scope of this paper, two major phenomena have happened at global and national levels. These are COVID-19 pandemic and the current unrest of Ethiopian civil war. Though analysis of their economic impact on the overall economy of the country and particularly to the aviation industry requires separate and thorough investigation and analysis. It is obvious that COVID-19 significantly affected the aviation industry, even though Ethiopian aviation industry tried to survive by reducing idle time of flights through transporting airfreight cargo by removing passenger flight seats. Taking necessary safety measures and fulfilling all mandatory requirements, Ethiopian airlines was pioneer to diversify its market share in transporting COVID-19 related medical equipment and first aid test kits (from Far East-China to European and African countries) before other airlines joining the market. Moreover, the aviation industry of Ethiopia has attempted to recover and increase passengers' volume frequently by taking the precautionary measures recommended by WHO, ICAO and IATA. Hence, market destination has significantly increased in all over the world except China (Ethiopian has reduced its 30 flights per week to less than 5 flights per week to China market due to COVID-19).

The unrest and sever war condition of Ethiopia is also another challenge to the aviation industry. This conflict between central and local regional governments has affected the economy. The entire economy has shifted to support the war. This severe civil war has tremendous economic, social and political impacts. Many government and non-government organizations including Ethiopia aviation are severely affected by this war. Particularly Ethiopian airlines has been blamed for transporting armaments for the ongoing genocidal war. In terms of economic impact, among 23 domestic and international airports four airports' operations (one international and three domestic airports) are totally stopped for more than one year due the ongoing civil war and one has stopped operation for about six months while the remaining eighteen airports are working with full capacity. Despite of those drawbacks, Ethiopian aviation had maintained staff without employee lay off. Availability of data is a constraint and further analysis of the unrest on the aviation industry is beyond the scope of this paper.

6.1 Fixed-effects model's estimation results

Here the time-invariant fixed effects model (Model 1) was estimated, and the estimation results are presented in Table 2. Overall, the model explains well variations in the labor use. This is demonstrated by the statistical significance of the F-statistics and the adjusted R^2. The explanatory variables considered in the labor use requirement model (lnL) are workload unit of passenger and freight cargo (lnY), average wages (lnW), capital (lnK), maintenance and repairing (lnM), energy (lnE), and time trend representing technology or shift in the labor use function over time. Among these variables workload unit of passenger and freight cargo, energy consumption, and technological change had statistically significant parameter estimates. These parameters can be interpreted as elasticities of percent change in lnL in response to a 1% change in the determinants of labor use.

Table 2. Estimation of Labor use based on the time invariant fixed-effects model

Explanatory variables	Coef.	Std. Err	p>|t|	95% Confidence	Interval
Log of aggregate output (lnY)	0.0564**	0.026	2.16	0.005	0.1079
Log of average wages (lnW)	-0.049	0.050	-0.98	-0.147	0.0497
Log of capital investments (lnK)	-0.013	0.021	0.61	-0.029	0.0550
Log of energy (lnE)	-0.123**	0.051	-2.42	-0.224	-0.0229
Log of maintenance and reparing (lnM)	-0.037	0.034	-1.09	-0.104	0.0298
Time trend (yr)	0.071***	.007	9.14	0.055	0.0857
Constant	-131***	15.36	-8.54	-161.4	-100.84
R2 adjusted	95.62%				
Corr(u_i, Xb) = 0.1118, F(6,188) = 121.95, Prob > F = 0.0000					
F-test that all u_i = 0: F(12, 188) = 89.76 Prob > F = 0.0000					

Note: ***, **, and * indicate significance at the 1%, 5% and 10% level respectively.
Source: Authors' calculations.

The estimation results show that a 1% increase in output services led to 0.0564% increase in the effective labor units. The estimated coefficient of energy consumption showed that other things being constant, a 1% change in lnE was associated with a -0.123% reduction in the labor use. Though the response is still low and inelastic. This result means that high energy consumption per effective labor hour (lnE) reduced the quantity of effective labor hour used. A negative energy coefficient suggests that labor and energy are substitutes. This shows that an increase in high-tech airport facilities and systems that require uninterrupted energy which can replace human resources' deployment.

The coefficient of time trend yr (0.071) is also positive and statistically significant. Thus, ceteris paribuss, labor use increased over time on average by 7.1% per annum across airports. It indicates increase in labour over time associated with expansion of services. A negative technological change effects was expected as a result of development of labour-saving technological change. The coefficient of wage is negative with the expected sign (as wages increase the demand for labor decreases) but not statistically significant. The labor use is not responsive to a change in the cost of labor.

The mean efficiency levels of all the airports were also estimated and is summarized in Table 3. The labor use efficiency level is estimated to be about 47.53% on average during the period 2002-17. In other words, airports' inefficiency levels of labor use on average were 52.47% higher than the required effective labor hours. The basic assumption of this model is that inefficiency is airport-specific but is constant over time. The variations in the airports effcieincy range between 4% and 100% showing that some airports were up to 96% inefficient or used more labor than the minimum required labor. The high standard deviation also shows the existence of extreme variations in efficiency among airports. In this model, the time effect is undermined, and this model can only work if the airport's management is not learning from its previous inefficiency.

Table 3. Summary of Labor use efficiency of the fixed-effects method (208 observations)

Variables	Mean (%)	Std. Dev.	Minimum (%)	Maximum (%)
Efficiency of Fixed-effects	47.53	0.32	3.91	100.00

Note: Authors' calculations.

6.2 Model separating persistent and transitory inefficiencies

In this section, a separation of time-invariant and time-varying inefficiency (Model 2) is analyzed based on Kumbhakar and Heshmati's (1995) model. The estimation result is shown in Table 4. With the exception of average wages almost all the other coefficients were statistically significant at the 1% level of significance. These estimated coefficients can be interpreted as percent change in labor hours in response to a 1% change in either of the four explanatory variables.

Taking the output variable, it implies that every 1% change in the fright and passenger services, ceteris paribus, was associated with a 0.166% change in labor use with a relatively inelastic response. It indicates increasing returns to use of labor for given capital and energy.

Similarly, the strong significant levels of capital, energy, and maintenance and repairing show that all other things being equal, a percent change in capital investments is directly related to a -0.071% reduction in labor use with a highly inelastic response. This shows that labor and capital are substitutable in producing airports services. This is consistent with Lachmann's (1947) explanation that substitutability focuses on producing the same output with a different combination of factors while complementarity depends on the 'technical rigidity' in changing the outputs than the factors of production. In addition, Paul (2019) maintains that capital and labor are predominantly characterized by complementarity. This is a paradox that means capital and labor can be substitutes. Finally, Mućk (2017) found that sectors with higher elasticity of substitution between capital and labor were a driving force in structural changes.

A percent change in energy per effective labor hour is directly related to a -0.265% change in the labor hour use. The other significant coefficient of the model is maintenance and repairing. A percent change in maintenance and repairing is directly related to a -0.172% change in the effective labor hours. The total coefficient value of the explanatory variables is -0.388 which is still inelastic.

Table 4. Estimation of Labor use results based on Kumbhakar and Heshmati (1995) (Model 2)

Explanatory variables	Coef.	Std. Err.	t-value	95% conf. Interval	
Log of aggregate output (lnY)	0.166***	0.028	5.97	0.111	0.221
Log of average wages (lnW)	-0.035	0.059	0.59	-0.081	0.151
Log capital investments (lnK)	-0.071***	0.023	-3.10	-0.117	0.026
Log of energy (lnE)	-0.265***	0.058	-4.54	-0.380	-0.149
Log of maintenance and repairing (lnM)	-0.172***	0.037	-4.67	-0.244	-0.099
Constant	9.13***	0. 711	12.84	7.73	10.54
Rho (R2)	90.83%				
Corr (u_i, Xb) = 0.3164	F (5,189) =90.24			Prob > F = 0.0000	
F-test that all u_i =0	F (12, 189) = 58.52			Prob > F = 0.0000	

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level respectively.
Source: Authors' calculations.

In general, one can hypothesize that capital, energy, and maintenance and repairing are highly related and influence effective labor use. According to this model new expansion in airports' infrastructure, additional facilities and system development, and proper coordination and integration of multi-system services contributes not only to an increase in services but also reduces the quantity of the effective labor used. In other words, the negative relationship between effective labor hours and capital, energy, and maintenance shows substitutability rather than complementarity in the labor use. This shows that the amount of productive labor hours has reached saturation. This implies an introduction of a high-tech and self-explanatory system, announcements, signages, capital intensive infrastructures have the potential to substitute the additional productive labor.

The time-invariant and time-varying inefficiency were separated according to Kumbhakar and Heshmati's (1995) approach and are given in Table 5. The estimated time-invariant and time-varying efficiency levels of all airports is 50.67% and 99.85% while the overall efficiency is 50.59%. In this model, the time-varying efficiency level is very high and close to one implying that in the short-run Ethiopian airports' management is practicing proper resource allocations per effective labor hours. Over time, related inefficiency is also temporary and will be recovered as time changes. Hence, the average magnitude of transitory inefficiency of labor use efficiency of airports is limited and can be managed by the current practices of the management.

Table 5. Mean efficiency of all airports based on Model 2 (Kumbhakar and Heshmati, 1995)

Model	Efficiency components	Mean	Std. Err.	Minimum	Maximum
Model 2	Time-variant	99.85	0.001	99.85	99.86
	Time-invariant	50.67	0.303	5.11	100.00
	Overall	50.59	0.303	5.10	99.86

Note: Author's calculations (2019).

On the other hand, the mean of persistent and overall inefficiency of effective labor use based on Model 2 were 49.33% and 49.41% respectively. In addition, efficiency levels of some particular Ethiopian airports' labor hours that minimum persistent and overall efficiency indicated almost the same (5.11% and 5.10%) efficiency level respectively. This is a very serious finding that some airports had very high levels of labor use persistent inefficiency (94.89%), on average, during the study period. This high level of persistent inefficiency is related to the management and other unobservable airport effects. Hence, such condition implies that without government interventions in the management of Ethiopian airports, persistent inefficiency will not change.

In contrast, some airports have high persistent efficiency (up to 100%). In reality, most Ethiopian airports are managing and administering their services following traditional ways of management and with the same airport leadership policies. An efficiency analysis was conducted for the low performing airports, but the panel data used is annual aggregate which could have an aggregate data effect. Accordingly, in the relative analysis some airports could reach saturation point. Efficiency improvements in such a situation require government interventions for putting in place a new system, policy, and management philosophy for the airport industry. This will lead to the overall economic transformation of the national economy.

Kumbhakar and Heshmati's (1995) model separates time-invariant and time-varying inefficiency. The model underlines that persistent inefficiencies are time-invariant and cannot be reduced without government interventions in changing policy and the strategic management of airports. Considering all time-invariant inefficiency as persistent inefficiency and the presence of unobserved airport effects leads to an upward biased persistent inefficiency (Parmeter and Kumbhakar, 2014). Even though time-invariant firm heterogeneity and time-invariant variables are specified as persistent, this model is still preferable for decomposing inefficiency as compared to several other model specifications.

6.3 The MLE estimation results

The maximum likelihood approach is the third model used for estimating labor use efficiency of Ethiopian airports. Table 6 shows that the estimation result. The model explains well the labor use. Even though the MLE generates higher efficiency, this model also requires a strong assumption of normality. It is supported by the robustness test statistics in Table 8.

Among thes explanatory variables the output, capital investments, energy consumption, and maintenance and repairing per effective labor hour have statistically significant effects. The coefficients can be interpreted as elasticities of percent change in labor use in response to a 1% change in either of the four variables. Accordingly, a 1% change in the output, ceteris paribus, brings about a 0.185% change in labor use with indicating increasing returns to scale.

Table 6. Labor use efficiency estimation results using the MLE approach

Explanatory variables	Coef.	Std. Err.	z	[95% Confid. interval]	
Log of aggregate output (lnY)	0.185***	0.028	6.50	0.129	0.240
Log of average wages (lnW)	-0.056	0.055	1.02	-0.052	0.164
Log of capital investments (lnK)	-0.068 ***	0.023	-2.94	-0.113	-0.023
Log of energy (lnE)	-0.259***	0.060	-4.28	-0.377	-0.140
Log of maintenance & repairing (lnM)	-0.132***	0.038	-3.43	-0.207	-0.056
Constant	8.510***	0.680	12.52	7.178	9.843
R2 adjusted	88.98%				
LR chi2(5) = 234.64 Log likelihood = -55.108 Prob > chi2 = 0.0000					
LR test of sigma_u = 0: chibar2(01) = 236.38 Prob >= chibar2 = 0.000					

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.
Source: Authors' calculations.

The coefficient of capital investments per effective labor hour shows that, a percent change in capital investment is associated with a -0.068% reduction in labor deployed. This also shows that the possibility of substitutability of capital and labor is reconfirmed in the MLE model.

The coefficient of energy shows that every percent change in energy is highly associated with a -0.259% change in labor use. This implies that higher energy cost will result in a significant reduction in the quantity of the effective labor labor used. Labor use and energy are substitutes to a certain extent in production of services. Similarly, increase in maintenance and repairing per effective unit of labor also is related to a 0.132% change in the labor used. Hence, uninterrupted maintenance and repairing of airport infrastructure, facilities, systems, and services can complement labor use. The coefficient for wage as expected is negative and statistically insignificant.

Table 7. Mean Labor use efficiency of all airports based on MLE method (Model 3)

Model	Efficiency components	Mean	Std. Dev.	Minimum	Maximum
Model 3	MLE-Residual	99.90	0.0006	99.90	99.91
	MLE-Persistent	49.65	0.2963	5.89	100.00
	MLE-Overall	49.60	0.2959	5.88	99.90

Note: Authors calculations.

The summarized mean results of the MLE approach are given in Table 7. The estimation results show that the mean time-varying efficiency level of all airports was 99.90% while the mean time-invariant persistent and overall efficiency was 49.65% and 49.60% respectively. Thus, the overall labor use efficiency of airports was approximately 49.60% which is 50.40% higher than the minimum required labor hours implying that persistent efficiency is very low and overuse of labor will continue unless some policy or interventions alleviate the inefficiency conditions at airports. Besides, efficiency varied across airports and the benchmarking airports scored more than 99% while the persistent efficiency levels of least efficient airports scored as low as 5.89% which is 94.11% higher than the minimum required labor hour deployed. The extremely high level of inefficiency requires government attention. The ML method has higher efficiency as compared to other estimation methods. Hence, the ML estimation's results have relatively higher reliability and leads to conclusion and policy recommendations.

As shown in the estimation results, higher short-run or time-varying efficiency implies that Ethiopian airports are performing properly in allocating short-run resources and any time-varying inefficiency is also easily alleviated over time. However, low persistent efficiency which has a permanent effect needs government attention. This high level of persistent efficiency can be on the one hand due to an aggregate data effect even though the dominant assumption of this study comes from overall trends in airports' performance. On the other hand, the current level of these specific airports efficiency of labor hours reached the minimum input requirements given passenger and air freight cargo output and capital, energy, and maintenance and repairing factors of production per effective labor hour. This does not mean that the airports have reached the highest level of efficiency and instead it is a relative analysis of reaching saturation. Improvements in the national economic conditions significantly supports the air transport growth and stimulate specific airports in particular. Thus, an overall economic development will help airports to gain a momentum of growth and efficiency improvements across time.

6.4 Robustness test for the stochastic frontier models

Since the model specification test allow for investigation of the reliability of the estimated result, skewness test for normality was examined. The test results indicated that null hypothesis of no skewness is rejected implying that the model is in favor of a left skewed error distribution, and it is also verified that the model is properly specified with the Cobb-Douglas function. This robustness tests result supports estimating the stochastic frontier model.

Table 8. Skewness/kurtosis tests for normality

Model	Variable	Probability		Joint test	
		skewness	kurtosis	Chi2(2)	Prob>chi2
Maximum likelihood	Err.	0.0000	0.0012	28.85	0.0000
estimation (MLE)	Muf.	0.0000	0.3085	22.65	0.0000

Note: Authors' calculations (2019).

As required by the MLE model, the existence of the inefficiency was tested using the log-likelihood ratio (LR) test. The LR test result of 99.67 suggest that the null hypothesis of no inefficiency is rejected at the 1% level of significance thus proving the existence of inefficiency in the labor use. Thus, it is possible to analyze the level and condition of labor use of airports using the stochastic frontier model.

Table 9. Mean labor use efficiency of all airports based on FE, KH and MLE models (2002-17, 208 observations)

ID	Airports	Model 1 FE (%)	Model 2 KH (%)			Model 3 MLE (%)		
		LR-PE	SR-RE	LR-PE	OTE	SR-RE	LR-PE	OTE
1	AABIA	3.91	99.86	5.11	5.10	99.90	5.89	5.88
2	Dire Dawa In’lA	13.54	99.86	19.41	19.38	99.90	19.84	19.82
3	Mekelle In’lA	18.63	99.86	20.29	20.26	99.90	20.56	20.55
4	Bahri-Dar In’lA	18.57	99.86	22.31	22.27	99.90	22.05	22.03
5	Jimma DA	31.17	99.86	36.68	36.63	99.90	35.29	35.26
6	Gonder DA	27.17	99.86	33.96	33.92	99.90	33.21	33.18
7	Axum DA	36.33	99.86	43.65	43.59	99.90	42.83	42.79
8	Lalibella DA	51.90	99.86	58.48	58.39	99.90	55.43	55.38
9	Gambella DA	86.67	99.86	88.88	88.75	99.90	88.63	88.54
10	Arbaminch DA	56.95	99.86	59.51	59.42	99.90	54.96	54.91
11	Gode DA	100.00	99.86	100.00	92.25	99.90	100.00	99.90
12	Assosa DA	86.44	99.86	82.72	99.86	99.90	79.00	78.92
13	Jijiga DA	89.83	99.86	90.74	82.60	99.90	87.67	87.59
	Average	47.52	99.86	50.67	50.59	99.90	49.65	49.60

Note: Authors’ calculations.

In Table 9 the estimate airport efficiency of the three models is presented. The estimated mean efficiency of the time-invariant fixed-effects is 47.52% while the mean time-invariant efficiency of Kumbhakar and Heshmati (1995) and the MLE are 50.67% and 49.65% respectively. It is known that there is a difference in distributional assumptions and also in the time-varying and time-invariant airport heterogeneity assumptions which leads to different efficiency results. Kumbhakar and Heshmati (1995) and the MLE models show relative efficiency levels which means that effective labor hour use was 49.33% and 50.35% exceeding the minimum requirement of labor hours.

The mean efficiency of each airport based on FE model varied between 3.91% at Addis Ababa International Airport and 100% at the Gode Domestic Airport. Jijiga Domestic Airport had an efficiency score of 89.83%, Gambella Domestic Airport 86.67%, and Assosa Domestic Airport 86.44%. In contrast, there were also airports with lower efficiency levels, namely, Dire Dawa International Airport at 13.54%, Bahir-Dar International Airport at 18.57%, and Mekelle International Airport at 18.63% as the second, third, and fourth least efficient airports. Thus, the international airports had lower levels of efficiency implying that their inefficiency was higher than the minimum required labor hours. Such high inefficiency at large international airports compared to their small domestic counterparts is attributed to higher service quality and capacity requirements.

In KH and the MLE approaches the residual efficiency was separated from the persistent efficiency. Using the Kumbhakar and Heshmati’s (1995) or multi-step alternative model the highest estimation of long-run persistent efficiency among these airports was at Gode Domestic Airport at 100% followed by Jijiga Domestic Airport at 90.74%, Gambella Domestic Airport at 88.88%, and Assosa Domestic Airport at 82.72%. The lowest long-run persistent efficiency was at Addis Ababa Bole International Airport at 5.11%, Dire Dawa International Airport at 19.41%, Mekelle International Airport at 20.29%, and Bahri Dar International Airport at 22.31%. The remaining airports’ long-run persistent efficiency results ranged between 33.96% for Gonder Domestic Airport and Arbaminch Domestic Airport with a 59.51% level of efficiency.

On the other hand, the efficiency levels of airports using the MLE model showed significant variations between persistent and transitory efficiency at the airports. In relation to the time-invariant efficiency condition, the relatively better performing airports were Gode Domestic

Airport 100%, Gambella Domestic Airport 88.63%, Jijiga Domestic Airport 87.67%, and Assosa Domestic Airport 79.00%, while relatively lower performing airports were Addis Ababa International Airport at 5.89% efficiency, followed by Dire Dawa International Airport 19.84%, Mekelle International Airport 20.56%, and B/dar International Airport 22.05% respectively. The international airports including the national hub Addis Ababa Airport scored the least in labor use efficiency and had excess labor deployment.

In the three models, the same airports Gode, Jijiga, Gambella, and Assosa domestic airports scored better in terms of persistent efficiency while the other airports Addis Ababa Bole, Dire Dawa, Mekelle, and Bahri-Dar international airports scored lower in persistent efficiency. This shows that airports having a larger number of passengers and freight cargo services scored lower in persistence efficiency of labor hours. On the other hand, airports having smaller numbers of passengers had higher persistent efficiency of labor hours. The relatively low levels of economic activities at these domestic airports and the surrounding region resulted in a limited number of passengers being transported. Hence, the time-invariant persistent efficiency score between 90% and 100% does not necessary mean that there is no potential for further improvements in efficiency at these airports. With overall growth of the economy, additional air transport demand can be created. Following to the demand and passenger capacity the efficiency analysis can be investigated to examine the trend of labor input requirements.

The literature indicated that transitory inefficiency could change over time while persistent inefficiency remains constant over time or across airports unless there is an active policy on the management of the airports. Hence, in this study airports with higher persistent inefficiency will continue being inefficient unless the Government introduce structural airport policy changes for achieving the minimum labor requirement levels. This could include revising the employment and labor use policy for increasing labor productivity for which specific government interventions are needed for bringing about structural changes to reduce future inefficiency.

7. SUMMARY, CONCLUSION, AND RECOMMENDATIONS

This research focused on labor use efficiency for optimizing the minimum labor requirements which will help to reduce the cost-of-service production for airports. It used the panel data stochastic input requirement function with the concept of minimizing labor use in the production of airports' services production. It studied 13 international and domestic airports covering the period 2002-17. Variations in the labor use hours were explained by workload unit of passenger and freight cargo, average wages, capital investments, maintenance and repairing, and energy consumption. Time-invariant fixed-effects, multi-step and maximum likelihood estimation of time-invariant and time-varying inefficiency were use.

In the time-invariant fixed-effects model, the coefficient passenger and freight cargo, energy, and the time trend were statistically significant. The effects of passenger and freight cargo, capital, energy and maintenance and repairing on labor use were found statistically significant in the multi-step and in the MLE approaches. The negative and statistically significant results of capital, energy, and maintenance and repairing inputs showed that in the course of providing airport services these inputs also contributed to minimizing labor use more by substituting the role of labor than by complementing it. In other word, the study concluded that labor use and airport output were complementary hence expansion of airport facilities is recommended. Capital, energy, and maintenance and repair inputs substitute labor.

Labor use efficiency level of the fixed-effects method without distributional assumptions was estimated to be about 47.52% on average during the study period. The mean efficiency results from the multi-step model showed that long run persistent and overall efficiency was 50.67% and 50.59% respectively with a 99.86% residual efficiency level. The MLE estimation method showed that the mean time-varying efficiency level of all the airports was 99.90% while the time-invariant and overall efficiency was 49.65% and 49.60% respectively. Thus, the actual labor use efficiency of Ethiopian airports was approximately 49.60%. The mean labor use inefficiency of the time-invariant fixed-effects was 52.48% while the mean time-invariant labor use inefficiency of the multi-step model was 49.33%. Finally, the mean time-invariant labor use inefficiency from ML estimation was 50.40%. MLE's results seem higher than those of the first model and lower than of the second model. Since MLE is preferred model, this shows that labor hour use was 50.40% inefficient compared to the minimum required labor hours.

In all the three models the mean efficiency score of each airport shows that efficiency conditions varied across airports. Despite minor estimation differences, the relatively better performing airports were mostly domestic airports. International airports were least performing in terms of labor use efficiency levels which implies that they need to take lessons in the deployment of resources and should look at ways of reducing their costs. The relatively low levels of economic activities at some domestic airports and their surrounding region is a result of a limited number of passengers being transported and absence of cargo transport. Hence, the time-invariant efficiency scores between 90% and 100% do not necessarily mean that there is no further space for efficiency improvements. Airports can grow with an overall growth of the economy which ultimately will create an additional air transport demand and will further have space for enhancement of efficiency of labor hour.

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