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A Stochastic Frontier Analysis of the Human Capital Effects on the Manufacturing Industries' Technical Efficiency in the United States

By Salem Gheit[*]

This study seeks to establish substantive empirical evidence on the role of college and non-college labour in productivity through technical efficiency in the manufacturing sector in the U.S. economy. This investigation fits a Cobb-Douglas stochastic frontier function with inefficiency effects to a set of panel data for 15 manufacturing industries over the period from 1998 to 2019. The contribution of this paper lies in the application of the stochastic frontier analysis following the approach of Caudill et al. (1995) by estimating and testing stochastic frontier production functions, assuming the presence of heteroscedasticity in the one-sided error term (inefficiency), which provides robust estimates of the technical efficiency measures. This paper also contributes to the literature in the sense that it follows the Hadri (1999) approach and its extension for panel data, Hadri et al. (2003), assuming the existence of heteroscedasticity in both error terms (the one-sided inefficiency term and the two-sided symmetric random noise). The rationale for the double heteroscedasticity estimation is that it results in more accurate measures of the effects of the technical efficiency determinants. Therefore, it adds another layer of confidence in the economic analysis of the impact of human capital components on the manufacturing sector efficiency and by extension, its productivity. The stochastic frontier results show the effects of highly educated workers and low educated workers – proxied by college and non-college labour – on technical inefficiency. This is where the maximum likelihood estimates suggest that the increase in the percentage of the hours worked by college workers tends to contribute positively to technological efficiency in the U.S. manufacturing industries. While on the minus side, it can be noted that the rise in the share of the hours worked by non-college persons seems to have negative impact on efficiency in these industries.

JEL Codes: *J24, D24, C23, C24, Q12*
Keywords: *human capital, technical efficiency, stochastic frontier production, double heteroscedasticity, panel data*

Introduction

Skilled human capital has been widely recognised as efficiency-driver and growth-enhancing in advanced economies and underdeveloped economies alike. It is therefore regarded – according to the endogenous growth theories – as a crucial

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ingredient for innovation growth and as an endogenous factor in production (Ali et al. 2018, Mahmood and Alkahtani 2018, Lawanson and Evans 2019).

The advances in the theory of economic growth, especially the developments in endogenous growth models, lie in the assumption that the long-run growth is determined within the model. The main element in these models is the technological progress, which means that a purposeful research and application would certainly result in new and cutting-edge products and state-of-the-art methods of production, and would pave a way to adopting the superior technologies that have been contrived and originated, as well as those developed in other countries or sectors (Barro 2013).

In Romer's model (1990) human capital plays a special role, and it has been identified as the principal input to the research sector that produces new ideas and commodities which underlie technological progress (Barro and Lee 1994, Ogundari and Awokuse 2018). That is to say, human capital overcomes the limitations imposed on growth due to the diminishing returns to other inputs (labour (L) and capital (K)) (Arshed et al. 2021), and it promotes growth and development through the important externalities of knowledge stock through raising the productivity of both labour and capital, and providing the appropriate environment for the emergence of entrepreneurs, who implement and benefit from diffusing innovations in order to encourage quality over the quantity of children when fertility rates gradually fall down worldwide (Mathur 1999).

In this respect, there are three main types of conclusions to be considered: (a) studies that consider human capital as a fundamental factor of economic growth; (b) studies that stand for the assumption that human capital accumulation cannot clarify the difference in income distribution when using these findings at an international scale; and (c) studies that consider human capital as a result of economic growth (Loening 2002). However, having said that, the difficult question that seems to face economic policy makers is how to generate and stimulate a sustainable unintermittent growth using scarce, irreproducible, and exhaustible resources? The answer appears to lie in the role that technological progress can play, but it could be the case that technological progress will involve the greater use of depletable resources, unless there are new ways, yet to be invented, to economise the use of those inputs – which are not regeneratable – of production, to allow for per capita income levels and standards of living to rise in the long run (Grossman and Helpman 1994, Huffman 2020).

In line with the endogenous growth models, the contribution of human capital to growth, via innovating new ideas and imitating existing ones, was further examined by Vandenbussche et al. (2006) in their model. The main assumption in this respect is that relatively skilled workers are better suited to innovation activities, while imitation, which is a more unskilled-intensive activity, is fundamental in this model.

This is while bearing in mind that the absolute intensity of skilled labour in innovation, and unskilled labour in imitation, is not specifically required in the argument of Vandenbussche et al. (2006). Thus, the allocation of endogenous skilled and unskilled labour between innovation and imitation, and the impact of the two components of human capital, largely relies on the technological progress in the economy (Vandenbussche et al. 2006).

The argument also involves exploring the effect of the interaction between human capital, and the economy's distance to the frontier, where the model proposes that the effects of the interaction for higher education and the proximity to the frontier is positive, whereas for primary and secondary education it is negative (Ang et al. 2011). In addition, given the more basic and the less advanced technology that is in use in the less developed economies, there might be weaker demand for highly skilled labour and stronger demand for the basic level of skills embodied in workers (Hanushek 2013). By extension, this means that the effects of the interaction between primary and secondary education in an economy that is far from the frontier, is positive, owing to the reliance on imitating technologies and innovations produced in economies at – or close to – the frontier, which could be put down to the low cost of imitation in comparison with the high cost of innovation in the less developed countries.

Literature Review

The literature contains various definitions of what human capital exactly means, and it is commonly defined as " knowledge, skills, competencies, and attributes embodied in individuals which facilitate the creation of personal, social, and economic well-being" (Healy and Côté 2001). It is similarly defined by Armstrong and Taylor (2014) as the knowledge and skills and abilities of the people employed in an organization. This is where these two main components are being created, maintained and, most importantly, being applied by the employees when performing their work tasks (Mičiak 2019).

There are three main policy domains for which education is considered to be crucial: (i) the stock of skills in the economy, which is the centrepiece for the prospects of economic growth (Tran and Vo 2020); (ii) the distribution of the skilled people in an economy, which is a fundamental determinant for income inequality, especially with the high wage premium for skills; and (iii) the relationship between an individual's stock of skills and knowledge and their background, which is also a key factor of social mobility and societal progress (Burgess 2016, Huffman 2020).

Cross-country research had found that measures of cognitive skills are associated with economic growth; albeit, some economists were concerned about this, and contended that the evidence on this relationship between skills and growth is rather mixed (Ali et al. 2018). This is where some argue that previous research used unsuitable proxies for educational attainment. More precisely, they emphasise that neither the completed years of education nor the national rates of enrolment in schools can capture the skills of educated individuals; Alternatively, there are direct measures of cognitive skills that are being sourced from the international tests of maths and science abilities in 50 nations (Hanushek and Woessmann 2012).

In recent decades, a great importance has been given to the role of human capital in any economy. Especially, with the emergence of the knowledge economy, which has been derived from the revolution in information technology, innovation, and communication, in which human capital was regarded as the mainstay of this new economy (Gogan 2014).

A great deal of research highlighted, and investigated the impact of human capital on wages and earnings – which was regarded by Lebedinski and Vandenberghe (2014) as a proof that education and training can raise labour productivity – and this research was equipped with a variety of methods and approaches in the related strands of literature, which were utilised, so as to estimate human capital and its various impacts (Tchernis 2010, Pulyaeva et al. 2020).

On the whole, much of the current literature on growth and human capital confirms two major routes: (1) that countries with a larger stock of human capital have more capacity to grow faster, and (2) investing in schooling is a prerequisite and the foundation for human capital, which in turn, is the principal generator of ideas and new technology (Mirza et al. 2020).

In the main, there appears to be some accord on the above two points. However, Aghion et al. (2009) suggest that researchers, mostly, have no choice but to apply their methodologies on crude proxies for human capital stock, such as average years of schooling or enrolment rates in formal education in a nation. They, therefore, argue that the average years of education, as an indicator, is the result of individuals' decisions to have more education, while considering the future returns of that education. Thus, it is endogeneity that could be the main driver for this decision, and not the nation's investment policy, in it being persuasive, to lead these individuals to decide to have more education.

On the other hand, most of the literature on efficiency analysis and measurement has been linked with the seminal work of Farrell (1957) who was influenced by the ideas of measuring "technical efficiency" posited in Koopmans (1951), and the "coefficient of resources utilization" by Debreu (1951) and Nguyen (2010). This is where according to Koopmans (1951), a producer is said to be technically efficient if, and only if, the goal of producing more of at least one output without the need for producing less of another output, or using more inputs, is achieved. The concept of "technical efficiency *TE*" refers to the ability to maximise output from a given vector of inputs, or put it the other way around, it is the firm's ability to minimise input utilisation in the production function of a given vector of outputs (Coelli et al. 2005, Arazmuradov et al. 2014).

Producer's efficiency (technical, allocative) principally concerns the comparison between the optimum (maximum production possibilities, behavioural targets of producers; optimum cost, profit, revenue) and the observed levels of the producer's outputs and inputs. In other words, the comparison involves the ratio of the observed to the maximum potential output attainable given the available input. Conversely, it includes the ratio of the minimum potential to the observed level of input needed to produce the given output or a combination of the two (Kumbhakar and Tsionas 2020).

There are two constituents of economic efficiency, technical and allocative efficiency. According to Koopmans (1951), technical efficiency can be observed as; a production unit that is technically efficient if an increase in any output necessitates a reduction in at least one other output, or an increase in at least one input, and if a reduction in any input involves an increase in at least in one other input or a reduction in at least one output (Koliński et al. 2016).

By measures of efficiency, the economic performance of a producer is normally described using two terms: efficient or productive. Productivity mainly refers to the ratio of a producer's output to the same producer's input. Given the fact that producers, in the more likely event, would use several inputs to generate many outputs; therefore, productivity calculations would require the aggregation of these outputs and inputs in a valid economic manner, so that productivity stays the same, as being the ratio of the output to the input (Lovell 1993).

With respect to the effect of human capital on technical inefficiency, some studies implemented SFA, this is where Kneller and Stevens (2006) found out that technical inefficiency was negatively linked to the levels of human capital in 9 industries across 12 OECD countries over the years 1973-1991.

The reviewed literature suggests that higher levels of education are assumed to lead to higher levels of innovation (Fonseca et al. 2019), and therefore, higher growth rates (Lucas 1988, Romer 1990, Gregory et al. 1992, Hansen and Knowles 1998, Vandenbussche et al. 2006, Charochkina et al. 2020); this is in spite of the Bils and Klenow (2000) argument on the reverse causality between education and growth, where they state that the richer and faster growing countries find it easier than less developed countries to increase their spending on education because they have better institutions to improve the quality of the education system output (Aghion et al. 2009, Lutz et al. 2018).

However, some studies on human capital provide compelling evidence that primary and secondary levels of schooling tend to play a crucial role in promoting growth throughout developing countries (Krueger and Lindahl 2001), while on the other hand, higher education plays a more decisive role in more developed economies, (Petrakis and Stamatakis 2002). Other studies showed ample evidence at best, on the positive impact of human capital in boosting growth, where with using a regional dataset, it was found that primary education, in Spain for instance, is positively associated with higher growth in poorer regions, whereas secondary levels of education seemed to be more significant in strengthening and supporting growth in more affluent areas (Di Liberto 2007, Faggian et al. 2019, Mellander and Florida 2021).

In addition, considerable attention has been paid to examine the relationship between human capital and efficiency across the years, and sizeable empirical research has established marked positive quantifiable impact of human capital on efficiency, productivity and therefore growth (Dimelis and Papaioannou 2014).

Furthermore, it has been suggested that by the means of intensifying domestic technical innovations, productivity can be spurred on (Romer 1990, Aghion et al. 1998). By way of contrast, some empirical evidence, resulting from examining the interaction between human capital and productivity, has shown some ambiguity that has emanated from the divergent and contrastive outcomes of the human capital effect on productivity (Wei and Hao 2011).

The proposed rationalisation for the differences in the impact of human capital on growth across countries includes: (i) the significant skills underutilisation in some countries is caused by improper institutional environment, and by devoting the available skills in the wrong economic activities. (ii) The variations of the marginal returns of education are due to changes in the growth rates of demand for educated labour caused by different structural shifts, and by the policies in some countries, which are exposed to various technical developments derived externally. (iii) The distinct approaches and strategies followed in transferring knowledge have widely varied across countries, which gave rise to variant and diverse impacts on growth throughout nations (Pritchett 2001, Van Hiel et al. 2018).

Cörvers (1997) distinguished between two factors of human capital: intermediate and highly skilled workers and their effects on labour productivity. The estimates indicated the positive impact of both factors on productivity, and just the highly-skilled labour alone is proved to be the statistically significant component of human capital that positively affects productivity (Cörvers 1997).

In the economic literature there can be four distinct effects of human capital on productivity: worker's, allocative, diffusion, and research (Cörvers 1994, Cörvers 1997). Welch (1970) points out that the productive value of education stems from the "worker's effect" or "own productivity", which refers to the worker's ability to be more efficient in using the resources available on account of receiving more education. This effect represents the marginal product of education. The outcome of this would be the ability of these efficient workers are assumed to produce more physical output and switch the production possibility curve outward. Hence, the higher the proportion of intermediate or highly skilled workers, as opposed to low-skilled workers, in the whole combination of labour, the higher the efficiency and productivity levels. The second phenomenon is called the "allocative effect", which implies the worker's ability to acquire and decrypt information about other production inputs' costs and features, which in turn would change the use of specific inputs and consider the use of new inputs that had not been used before, as well as developing alternative uses of them, that is if a certain change in the worker's education has not occurred (Welch 1970).

The third impact is known as the "diffusion effect", which incorporates the adaptability of a better-educated worker to absorb and assimilate technological advancements and generate new production approaches in a faster manner (Nelson and Phelps 1966, Twum et al. 2021); thereby, higher education levels will facilitate the dispersion of technology, and provide a worker with the quality of being able to successfully opt for the more remunerative inventions that are to be quickly adopted, accommodated and employed (Bartel and Lichtenberg 1987, Adams 2018). This is where empirical evidence confirms that a well-educated and highly-trained labour force is fundamental in attracting and adapting technology investment; whereby, it leads to more technical change, and therefore, long-term economic growth (Bresnahan et al. 1999). Bassanini and Scarpetta (2001) also examined the impact of human capital on growth and observed significantly positive role of human capital across a selected group of OECD countries.

The fourth impact is believed to be "the research effect", which involves the crucial role of higher education, as an essential and vital factor in research, and the development of complex activities, which in turn entails intermediate and highly skilled workers to reach higher levels of technological knowledge in order to be able to increase the growth levels of productivity (Englander and Gurney 1994).

Methodology: Stochastic Frontier Analysis

In 1977 and in two independent papers, a stochastic frontier function for Cobb-Douglas case was specified and introduced by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). This specification assumes that inefficiency represents a component of the error term in the orthodox production function (Maudos et al. 2003). Thus, the error term contains inefficiency effects along with other factors effects which are uncontrollable by the production unit such as natural disasters, strikes, sickness, and so forth.

The core idea is that all production units are expected to perform either below or exactly on the frontier line, this is where none of the production units is expected to perform at any level above the frontier, simply because they do have the capacity to do so, due to several factors, including technological limitations.

The most widely used frontier analysis is the output-oriented stochastic frontier approach, where the basic idea involves the existence of an unobserved best-practice production frontier corresponding to the set of maximum attainable output levels for a given combination of inputs. However, most of the time actual production comes about below the best-practice of production frontier because of technical inefficiency.

Technical efficiency is $$TE = \frac{The\ observed\ output}{The\ potential\ maximum\ output} = \frac{Y^A}{Y^M}$$

Where $$0 \leq TE_{it} \leq 1$$

Therefore
$$\therefore Y^A = Y^M.TE \ \ = f(x;\beta).TE$$

The observed output is $$Y^A = f(x;\beta).exp(v).exp(-u)$$

Where:
$v \leq 0$ "noise" error term, (normal distribution).
$u \geq 0$ "inefficiency error term", (half-normal distribution).

and

$f(x;\beta) \rightarrow deterministic\ kernel$
$exp(v) \rightarrow the\ effect\ of\ exogenous\ shocks\ on\ output$

$exp(-u) \rightarrow inefficiency$
$f(x;\beta).exp(v) \rightarrow stochastic\ frontier$

The basic idea of deterministic frontier and stochastic frontier can be illustrated as follows:

OLS:	$q_i = \beta_0 + \beta_1 x_i + v_i$
Deterministic:	$q_i = \beta_0 + \beta_1 x_i - u_i$
SFA:	$q_i = \beta_0 + \beta_1 x_i + v_i - u_i$

Where:

$$q_i = exp(\beta_0 + \beta_1 \ln x_i) \times exp(v_i) \times exp(-u_i) \quad \text{Equation (1)}$$
$$= Deterministic\ Component \times Noise \times Inefficiency$$

The distance by which a firm lies below its production frontier is the measure of its inefficiency. However, Farrell (1957) proposed a decomposition of economic efficiency into technical efficiency and allocative efficiency where the former is meant to measure the firm's ability to reach the maximum level of output given a vector of inputs, whereas the latter refers to the firm's ability to use the inputs available with optimal shares given their market prices. That is to say:

$$Economic\ Efficiency = Technical\ Efficiency + Allocative\ Efficiency$$

Measuring technical efficiency can be achieved through two frontier methods. The first approach is named as the Data Envelopment Analysis (DEA) which is a non-parametric method, while the other is referred to as the Stochastic Frontier Analysis (SFA) which is regarded as a fully parameterized model, and both are categorized as frontier approaches, yet no excogitated formulation has been introduced to merge these two in one single analytical framework.

The rationale of these techniques is that efficiency of production is determined by the distance between the actual production and the best practice production frontier (Dimelis and Papaioannou 2014). Technically speaking, the two-component error term are the symmetric term (v_{it}) which demonstrates the noise, and the asymmetric term (u_{it}) that explains technical inefficiency.

In addition, the *SFA* provides a technique where panel data can be applied and encompasses other external environmental factors which could affect technical inefficiency related to the decision making unit (Arazmuradov et al. 2014). Another advantage of *SFA* is that it considers the effects of the random shocks on GDP.

However, the downside of this approach is that it requires an exact functional form (which is not given much of attention) of production function and the distribution assumption on the error term (Greene 2008).

Following Aigner et al. (1977) approach and Meeusen and van Den Broeck (1977) methodology, in particular the Battese and Coelli (1995) specification, technical inefficiency can be estimated from the stochastic frontier and simultaneously interpreted by a group of a firm's specific characteristic variables. The benefit of this methodology is that it escapes the problem of inconsistency which results from applying the two-stage method when investigating determinants of inefficiency (Diaz and Sánchez 2008).

Thus, growth in productivity will be mainly attributed to technical change or in other words, *TFP* growth is interpreted as the movement of the frontier function (Maudos et al. 2000). Still, the estimates would be regarded as biased owing to the presence of technical inefficiency.

On top of that, and despite the nonoccurrence of technical inefficiency, the estimates of the accounting growth of TFP would be affected by the allocative inefficiency which causes them to be biased again, and therefore it will affect the measurement of human capital impact on growth. On the other hand, non-parametric approaches (e.g., Data Envelopment Analysis DEA) do not impose any restrictions on production function. However, they are not flawless, because they cannot segregate the inefficiency effects from the white noise (Dimelis and Papaioannou 2014).

To avoid the prejudice problem, and considering the existence of inefficiency, the frontier techniques are more efficient tools to use. One of the SFA pros is that it allows for the estimation of firm-specific inefficiency according to the methodology proposed by Jondrow et al. (1982) based on the conditional expected value of u_i given e_i (Hadri et al. 2003).

The general form of Cobb Douglas stochastic frontier production function can be observed as follows:

$$Y_{it} = \acute{\beta} x_{it} + E_{it} \qquad \text{Equation (2)}$$
$$E_{it} = V_{it} - U_{it} \qquad \text{Equation (3)}$$

Where, Y_{it} denotes the appropriate function (logarithm) of the production for the ith sample firm, $(i = 1, 2, \dots \dots .\mathrm{N})$ in the tth time period $(t = 1, 2, \dots \dots ..\mathrm{T})$ x_{it}, represents the $(1 \times k)$ vectors of appropriate function of the explanatory variables associated with the ith sample firm in the $\mathbf{t^{th}}$ period (the first element would generally be one) $\acute{\beta}$, represents the $(k \times 1)$ vector of the coefficients for the associated independent variables in the production function which need to be estimated.

The term $(V_{it} - U_{it})$ is the composed error term. V_{it}, represents the random variables which are assumed to be independently, identically, and normally distributed with zero mean and constant variance. $N(0, \sigma_v^2)$, and it is independent of the U_{it}.

U_{it}, represents non-negative random variable that are assumed to be identically, independently, and normally distributed with zero mean $N(m_{it}, \sigma_u^2)$ and it is used to capture technical inefficiency.

According to Coelli et al. (2005) the above Cobb-Douglas stochastic frontier function can also take the following form:

$$Y_i = exp(\beta_0 + \beta_1\, ln\, x_i) \times exp(v_i) \times exp(u_i) \qquad \text{Equation (4)}$$

Where:
$exp(\beta_0 + \beta_1 \ln x_i)$ = deterministic component
$exp(v_i)$ = noise
$exp(u_i)$ = inefficiency
and according to Kokkinou (2009) the forenamed function can be rewritten as:

$$y_i = \mathrm{F}(x_i\beta) \times exp(v_i - u_i), u_i \geq 0 \qquad \text{Equation (5)}$$

Where:

u_i denotes for the shortfall of output from the frontier as previously defined. Since v_i is the random statistical noise, a symmetric distribution is usually assumed for v_i. In the same time, u_i which represents technical inefficiency term is assumed to be one-sided, it is also non-negative for the production frontier, and non-positive for the cost frontier. In most of the cases of production frontier, the distribution of [e_i = (v_i - u_i)] will be skewed, keeping in mind that the composed error (e_i) will (v_i + u_i) in the case of cost frontier

With respect to technical efficiency of a given firm (i), TE_i , it can be defined as the ratio of its mean production (in original units), given its realized firm effect, to the corresponding mean production if the firm effect was zero (Battese and Coelli 1988). In that, it measures the difference in the observed output of the firm relative to the output produced by a fully efficient firm using the same amount of inputs.

The value of TE_{it} can be defined and estimated through the following form;

$$TE_i = \frac{E(Y_{it}^*|U_i, x_{it}, t=1,2,\ldots.)}{E(Y_{it}^*|U_i=0, x_{it}, t=1,2,\ldots.)} \qquad \text{Equation (6)}$$

$$TE_{it} = \frac{y_{it}}{exp(x_{it}\hat{\beta} + v_{it})} = \frac{exp(x_{it}\hat{\beta} + v_{it} - u_{it})}{exp(x_{it}\hat{\beta} + v_{it})} = exp(-u_{it}) \qquad \text{Equation (7)}$$

The value TE_{it} is necessarily expected to be between one and zero. Thereby, the closer the observed point is to the frontier, the higher is the technical efficiency of a firm. If, for instance, a firm's technical efficiency is 0.75, then it implies that the firm realizes, on average 75% of the production possible for a fully efficient firm having comparable input values (Battese and Coelli 1988).

The analysis of production function in the stochastic frontier framework concerns two steps. The first step requires the use of the maximum likelihood to estimate the frontier model. In the second, measures of inefficiency or efficiency are constructed using the estimated frontier model.

Following Caudill et al. (1995), a multiplicative heteroscedasticity is assumed in the one-sided error term u_i only. However, it is argued by Hadri (1999) that in the cross sectional data, the two-sided symmetric error term can also be affected by size-related heteroscedasticity. Ignoring this assumption is likely to lead to a misspecified maximum likelihood function due to heteroscedasticity being not integrated in the estimation which yields inconsistent estimated parameters (White 1982).

To integrate heteroscedasticity in the symmetric noise term vi, at the same time with the one-sided inefficiency term u_i, the model H_{UV} (Heteroscedasticity in u and v) is specified where we now have a vector of non-stochastic regressors related to the firm size characteristics to be included in the v_i side along with a vector of unknown parameters to be estimated. Also, the values of both σ_i^2 and λ_i will be determined as $\sigma_i^2 = \sigma_{vi}^2 + \sigma_{ui}^2$ and $\lambda_i = \frac{\sigma_{ui}}{\sigma_{vi}}$. where each of σ_{vi} and σ_{ui} comprise a set of explanatory variables that affect both v_i and u_i respectively.

The SFA methodology enables the assessment of different variables' effects on efficiency and the extent of their importance in performance. In this field, unlike other areas, the model's parameters estimation is not the ultimate intent per se. Instead, estimating and analysing the industries' inefficiencies are objectives of greater interest (Greene 1990). Therefore, the rationale for choosing the SFA is that estimating average production functions by conventional regression methods rather than frontiers hinges upon the assumption that all units of production are efficient, which means that if this assumption does not hold, the parameters estimated would be affected, and consequently the importance of human capital as well.

Moreover, estimating *TFP* through the growth accounting approach (Solow's approach) implies all individuals are efficient, therefore, any estimated growth in *TFP* would be interpreted as a shift of the frontier function (technical change), but in the existence of technical or allocative inefficiency, the estimated *TFP* would be biased, and accordingly, the assessment of human capital contribution in efficiency will lack accuracy (Maudos et al. 2003). Thus the use of SFA is necessary to take into account any possible presence of inefficiency and to avoid the bias resulting from the estimation by conventional methods (Färe et al. 1997, Taskin and Zaim 1997).

Heteroscedasticity in the Stochastic Frontier Production Functions

As noted by Caudill et al. (1995) that the measures of inefficiency are based on the residuals derived from the stochastic frontier estimation and they noticed that these residuals tend to be sensitive to errors of specification and to a higher degree in the stochastic frontier models. They argue that this problem of sensitivity will affect the accuracy of the inefficiency measures. To tackle this issue, they proposed that researchers might need to test for heteroscedasticity presence, and if present, they can correct for heteroscedasticity in the one-sided error term (inefficiency) (Zhang 2012).

Furthermore, Hadri (1999) suggested that the two-sided error term might also suffer from heteroscedasticity, and if that was to be ignored, then the maximum likelihood estimates will be inconsistent and inaccurate. Therefore, he advises to test for heteroscedasticity in both error terms, and if present, the appropriate corrective procedures must be applied on both terms to obtain the correct and robust estimators (Hadri et al. 2003).

In the panel data models, and when v is heteroscedastic, the estimates of the parameters in the frontier function and those of technical inefficiency function are consistent under both the time-invariant fixed-effects and the random-effects methods. Whereas, in both the maximum likelihood approach, the estimates consistency is preserved only if the time trend observed (T) in the panel is relatively large in comparison with individuals (N).

In the time-varying panel data models, and when v is heteroscedastic, with the correction of Kumbhakar (1990), Cornwell et al. (1990), and Lee and Schmidt (1993) methods, the imprecision in the estimates can be solved and the MLE can be considered even if the (N) is large (Zhang 2012). According to Caudill and Ford (1993), Caudill et al. (1995) and Hadri (1999) a term of multiplicative heteroscedasticity is incorporated into the one-sided error term with the variance $\sigma_u^2 = \exp(\gamma' Z_{it})$.

Panel Industry-Level Data

It is scarcely needed to underscore the advantages of panel data over other types of data. However, besides its benefits for being more informative and more dynamic, with less collinearity between variables. The panel data allows researchers to control for heterogeneity of individuals or entities in a proper way both via the estimating methodology and by the specifications of the model.

In addition, if one has panel data, they can avoid three major problems in the stochastic frontier estimation, including (a) the variance of the technical inefficiency distribution conditional on the whole error term does not disappear as the sample size increases. (b) the segregation of the technical inefficiency from the statistical noise and the estimation of the model needs specific assumptions about the technical inefficiency and statistical noise distributions, but it is not obvious yet how robust the results of the estimation to these assumptions. (c) it may be inaccurate to assume that inefficiency is independent of its explanatory variables if the firm/industry knows the level of its inefficiency.

A 22-panel data for a 15-industry cluster was extracted from the Bureau of Economic Analysis (BEA) on *Value-Added Output, College Labour Inputs, Non-college Labour Inputs, ICT Capital, R&D Capital, Software Capital, Energy, Materials, Services Inputs, Labour Inputs, Gross Output, and Other Capital Inputs.*

It is noteworthy to state that the gross output concept differs from the sectoral output concept used by the BLS in its industry-level *TFP* statistics. The sectoral output methodology elides intermediate production and purchases which come from within the industry (intra-industry transactions) from either outputs or inputs (Schreyer 2001).

The 3-digit 15 industries along with their $NAICS$ codes are as follows:
(1) Machinery (333), (2) Computer and Electronic Products (334), (3) Food and Beverage and Tobacco Products (311, 312), (4) Textile Mills and Textile Product Mills (313, 314), (5) Apparel and Leather and Applied Products (315, 316), (6) Paper Products (322), (7) Chemical Products (325), (8) Wood Products (321), (9) Primary Metals (331), (10) Electrical Equipment, Appliances, and Components (335), (11) Fabricated metal products (332), (12) Petroleum and coal products

(324) , (13) Plastics and rubber products (326). (14) Motor vehicles, bodies and trailers, and parts (336), (15) Furniture and related products (337).

The data is observed annually and measured as indexes of each of the real value-added output – as a dependent variable – and capital inputs, labour inputs and a measure of intermediate inputs including energy, materials, and purchased services as independent variables, knowing that all variables are converted into logarithm values. The lack of accessible sources that provide firm-level data on the U.S. manufacturing sector is the main problem the researcher had faced when collecting this panel data.

As regards labour composition, the contribution of labour to output growth is decomposed into demographic characteristics which account for the contribution of the college-educated workers and those workers who did not attend college. The benefit of this adjustment is to allow for the contribution of labour to reflect the changes in the workers' skills level composition and the number of hours worked in each industry over the years.

Variables for the Stochastic Frontier Production Functions

The variables included in the frontier production function in shorthand are as follows:

Ln VA = Value-Added output. It is the aggregate value-added growth which is the sum of share-weighted value-added growth by industry. Value- added output represents compensations of employees, taxes on production and imports, fewer subsidies, and gross operating surplus. It does not include intermediate inputs.

Ln K = Capital services: are the services derived from the physical assets stock and intellectual property assets. In other words, capital services reflect the flow of productive services provided by an asset that is employed in production. The value of capital services is the number of services provided by an asset (multiplied by) the price of those services.

Assets such as:

1- Fixed business equipment and structures.
2- Inventories, lands.

Ln L = Labour inputs which are denoted by hours at work by age, education, and gender group are weighted by each group's share of the total wage bill. Labour hours represent the annual hours worked by all persons employed in an industry.

Labour inputs by industry in the industry-level production accounts published jointly by the Bureau of Economic Analysis BEA and Bureau of Labor Statistics BLS are measured as Tornqvist quantity indexes of hours worked classified by gender, age group, and education group. The education group include grade school, less than high school degree, high school degree, some college, college degree, and more than a college degree.

The dollar value of this work is labour compensation. The implicit price of labour input is the labour compensation divided by the quantity index. The labour compensation includes the payroll + any supplemental payments. The payroll includes salaries, wages, bonuses, commissions, dismissal pay, vacation and sick leave pay...etc.

Labour compensation is the cost to the employer of securing the labour services, and the unit labour costs describe the relationship between the compensation per hour and real output per hour (labour productivity). To estimate college and non-college labour, the BEA and BLS form Tornqvist indexes for hours worked for college and non-college workers by industry.

Ln IM = Intermediate inputs: consist of the goods and services – including energy, raw materials, semi-finished goods, and services that are purchased from all sources – that are used in the production process to produce other goods or services rather than for final consumption.

They represent a large share of production costs, and it is found that the substitution among inputs (intermediate inputs included) has its impact on the changes in productivity.

Ln E= Energy inputs: the amount of fuel, electricity, and other forms of energy used to produce output.

Ln M= Material inputs: the number of commodities, in the form of intermediate materials, used to produce output, also known as materials inputs.

Ln S = Purchased Service inputs: the amount of outside contract work used to produce output.

The determinants of efficiency included in the inefficiency model are in shorthand as follows:

Ln ICTK = ICT capital stock: information or data that has intrinsic value which can be shared and leveraged within and between organisations.

The information technology capital assets consist of communications equipment, mainframe computers, personal computers, direct access storage devices, printers, terminals, tape drives, storage devices, and integrated systems.

Ln RDK = R&D Research and Development capital stock.

Ln College = College labour input. It includes workers with a bachelor's degree and above.

Ln Non-college = Non-college labour inputs. It represents the remainder of workers after bachelor's degree holders and above is subtracted from the total.

Ln Other K = represents other capital which includes about 90 types of other capital equipment and structures, inventories, and land according to the BEA/BLS integrated industry-level production accounts reports where office and accounting, machinery, photocopying and related equipment, medical equipment, electromedical instruments, and nonmedical instruments are redefined by the BEA measures and included in other capital assets.

Econometric Results and Economic Analysis

Table 1 shows the output of the stochastic frontier production function results and inefficiency models obtained from the $Nlogit5$ Econometric software, following the CFG (1995) approach assuming the presence of heteroscedasticity in the one-sided inefficiency term in the H_U *models (1, 2, and 3),* and following the Hadri (1999) and Hadri et al. (2003) approach and its extension for panel data, which includes the double heteroscedasticity assumption in the H_{UV} *model (4).*

As can be seen, the estimated parameters of the frontier production function are represented in this table by labour inputs (*L*) and capital inputs (*K*). The lower section of the table shows the estimated parameters of the technical inefficiency function which has been estimated contemporaneously using the *College* and *Non-college* labour indexes, the *ICT* capital, *R&D* capital, and *Software* capital indexes as principal explanatory variables in technical inefficiency changes. Inefficiency is modelled as dependent on the level of *human capital*, *ICT* capital, *R&D* capital, and *Software* capital in industry *j* at time *t*.

Table 1. *Maximum Likelihood Estimates in the U.S. Manufacturing Industries during the Period (1998-2019) Cobb-Douglas Stochastic Frontier Production Functions*

Cobb-Douglas stochastic frontier production function: dependent variable Ln VA= (ln Value Added Output)	Model 1 Two- input and time-invariant stochastic frontier production function (correction for heteroscedasticity in u only)	Model 2 Two- input and time-varying stochastic frontier production function (correction for heteroscedasticity in u only)	Model 3 Three- input and time-varying stochastic frontier production function (correction for heteroscedasticity in u only)	Model 4 Three- input and time-varying stochastic frontier production function (correction for heteroscedasticity in both u and v)
	Parameter (robust SE)	Parameter (robust SE)	Parameter (robust SE)	Parameter (robust SE)
Constant	-0.083 (0.511)	0.211 (0.662)	0.516 (0.670)	0.477 (0.621)
Ln K input	0.500*** (0.084)	0.464*** (0.095)	0.443*** (0.100)	0.293***(0.112)
Ln L input	0.539*** (0.065)	0.510*** (0.077)	0.357*** (0.106)	0.643***(0.072)
Time input	-	0.749 (0.002)	0.730 (0.002)	0.002 (0.002)
Ln IM = Ln Intermediate Inputs	-	-	0.108 (0.078)	0.016 (0.040)
Inefficiency function				
Constant	-4.159 *** (.112)	-4.142***(.13155)	-4.143*** (.132)	31.937 (23.818)
Ln_College_Labour	-14.022***(3.795)	-12.147***(4.218)	-12.667***(4.688)	-9.356*** (2.404)
Ln_Non-College_Labour	5.280*** (1.703)	5.06042** (2.552)	4.334 (2.769)	6.143** (2.500)
Ln_ICT_Capital	-1.678* (0.965)	-1.578 (1.089)	-1.185 (1.187)	-1.671** (.771)
Ln_R&D_Capital	-	-0.426 (4.080)	-0.791 (4.542)	-0.697 (4.415)
Ln_Software_Capital	1.640 (1.208)	3.556** (1.721)	3.364** (1.689)	3.021** (1.241)
Ln_Materials	3.567*** (1.287)	5.321*** (1.878)	6.171*** (2.156)	4.110*** (1.061)
Ln_Purchased_Services	-	-1.321 (1.273)	-1.045 (1.412)	-1.772* (.931)
Ln_Other_Capital	-	-10.546 (6.900)	-11.178 (7.040)	-8.045(5.849)
Log-likelihood function	134.2216	142.3402	144.4410	170.1102
Parameters in variance of v (symmetrical term)				
Constant	-	-	-	13.059** (5.805)
Ln RD Capital	-	-	-	-4.443*** (.901)
Ln Other Capital	-	-	-	9.007*** (2.589)
Ln Non-college Labour	-	-	-	-4.329*** (1.382)
(Gamma) γ	0.879	0.880	0.887	0.915
σ = Sqr[(s^2(u)+s^2(v)]	0.359	0.364	0.375	0.422
N. obs. [K]	330 [10]	330 [14]	330 [15]	330 [19]
Deg.freedom for inefficiency model	6	9	9	9
Deg.freedom for heteroscedasticity	5	8	8	8
LR test results 1- H_0 = Cobb-Douglas stochastic frontier production function	Accept H_0 at 95%	Accept H_0 at 95%	Accept H_0 at 95%	Accept H_0 at 95%

2- H_1 = Translog stochastic frontier production function				

Notes; 1- See Table 1 for the definitions of variables. 2 - * Significant at 90% level of significance.
3 - ** significant at 95% level of significance.4- *** significant at 99% level of significance.
5- Figures in parentheses are robust standard errors.

Regarding the effects of human capital – proxied by *College* and *Non-college* labour – on technical inefficiency, the maximum likelihood estimates suggest that the increase in the percentage of the hours worked by *college* workers tends to contribute positively to technological efficiency in the U.S. manufacturing industries. On the other hand, it can be noted that the rise in the share of the hours worked by *non-college* persons seems to have negative impact on efficiency in these industries. Human capital is included in the model as efficiency determinant due to the role that it could play indirectly through efficiency by its impact on the absorptive capacity.

From the reported results of the *generalised likelihood ratio test LR* in Table 2, in *model (1)* it can be concluded that the null hypothesis was accepted at 95% level of confidence with a preference to the *Cobb Douglas* functional form to represent this panel data. According to the latter, it would seem to be possible to distinguish the significant and positive effects of two inputs *labour* (*L*), and *capital* (*K*) on output in the fitted frontier production function. From the literature point of view, this appears to be reasonable and consistent with the conclusions reached in previous studies with similar weights of labour and capital coefficients where the value of output and inputs were deflated by the appropriate price indexes.

The information and communication technology capital *ICT* shares appear to be of significant impact and contributed positively to minifying technical inefficiency in the U.S. manufacturing industries. From an economic perspective, it should be also marked that economies that are largely endowed with a high proportion of skilled labour of the total labour force would bear the high cost of skilled labour because of the wage bills. These economies are more able to find the optimal level of technology to enhance the level of efficiency to their labour and capital by employing more sophisticated technology. Whereas those countries with high percentages of less skilled labour find it easier to deploy less advanced technologies and the level of capital accumulation will be lower. However, the optimal combination of technology and capital is largely determined by the endowment of human capital.

In Table 1 the value of the variance parameter ($Gamma$) (γ) which lies between 0 and 1 is equal to 0.879 in *model (1).* It, therefore, confirms the presence of stochastic technical inefficiency and that it indicates to its relevance to obtaining the adequate representation of the data. The same analysis applies to the $gamma$ parameter (γ) in the other *models 2, 3, and 4.*

From this, if $Gamma = 0$, then the technical efficient capacity utilisation $TECU$ value is expected to score 1 ($\sigma_u^2 = 0$), meaning that the deviations from the frontier can neither be ascribed to the presence of technical inefficiency nor to capacity underutilisation, and if $Gamma = 1$, where the value of $TECU = 0$, ($\sigma_v^2 = 0$), it will indicate that deviations from the frontier can be attributed to technical inefficiency and capacity underutilisation (Pascoe et al. 2003). In case

$gamma$ is larger than 0 and less than 1, then deviations can be explained by both technical efficient capacity utilisation and the random component (Battese and Corra 1977).

In addition, the production function inefficiency is calculated by the error term using the composite error term of the stochastic frontier model which is defined by $\gamma = \frac{\sigma_u^2}{(\sigma_v^2+\sigma_u^2)}$. This is where it represents a measure of inefficiency level in the variance parameter which ranges from 0 to 1.

In this case since $Gamma \approx 0.88$ (yielded either from $\frac{\sigma_u^2}{\sigma^2}$ or $\gamma = \frac{\sigma_u^2}{(\sigma_v^2+\sigma_u^2)} = \frac{.11393}{.12955} = 0.879$). That indicates that the variance of the inefficiency effects is a significant term of the total composite error term variance, and therefore the deviations from the optimal level of output in the U.S manufacturing industries subject to study is due to both the random exogenous factors and inefficiency existence in the production processes. In other words, this implies that the stochastic production frontier is significantly different from the deterministic frontier which does not comprise a random error. The same logic applies to the *gamma* values in *models 2, 3, and 4,* where it equals = 0.880, 0.887, and 0.915 respectively.

Table 2. *Summary of the Generalised Likelihood-Ratio Tests of the Null Hypothesis*

Model 1: Null Hypothesis, H_0	Production Function Form	Log Likelihood Function	P	Critical Values of the $\chi 2$ Distribution
H_0: βij = 0, i = 1,…,6				
	Translog	138.457	99% ρ = (0.01)	16.8*
	Cobb – Douglas	134.221	95% ρ = (0.05)	14.5*
	LR Test	8.472	90% ρ = (0.1)	10.7*
Model 2: Null Hypothesis, H_0				
H_0: βij = 0, i = 1,..,8				
	Translog	144.846	99% ρ = (0.01)	20.1*
	Cobb - Douglas	142.340	95% ρ = (0.05)	15.5*
	LR Test	5.011	90% ρ = (0.1)	13.4*
Model 3: Null Hypothesis, H_0				
H_0: βij = 0, i = 1,..,8				
	Translog	148.054	99% ρ = (0.01)	20.1*
	Cobb - Douglas	144.441	95% ρ = (0.05)	15.5*
	LR Test	7.226	90% ρ = (0.1)	13.4*
Model 4: Null Hypothesis, H_0				
H_0: βij = 0, i = 1,..,8				
	Translog	171.418	99% ρ = (0.01)	20.1*
	Cobb - Douglas	170.110	95% ρ = (0.05)	15.5*
	LR Test	2.616	90% ρ = (0.1)	13.4*

Bearing in mind that skills are aggregated with a skill-specific share in total labour remunerations. With these suggested particular measures of labour and capital – which can be very often constrained by sources and data to establish such distinction and cover all labour and capital inputs – the different impacts of the technological progress resulting from improved (capital, intermediate inputs, and labour or human capital) need to be reflected in the varying contributions of each of these inputs.

Moreover, the residual or the disembodied technical change will be captured in *TFP* growth, and that is how *TFP* gathers up the spillover effects on output growth which came about production factors improvements. The key point here is that growth in *TFP* cannot only be attributed to technological progress. To put it another way, there are other determinants including; changes in efficiency, measurement errors, cost adjustments, cyclical effects, economies of scale, that could give rise to *TFP* increment.

Model (2) demonstrates the time-varying version of the Cobb-Douglas stochastic frontier production function presented in model (1). However, in this model the observed years (T) were factored in the model in order to proxy for technological change (the so-called Hicksian neutral) given the period of time over which this set of data was observed is 22 years. The time-varying technical inefficiency is obtained via the same normalisation for each year of the panel in the time-invariant case which ensures that $\hat{u}_{it} \geq 0$ and that is to say, $TE_{it} = exp(-u_{it})$. Where $\hat{u}_{it} = max_i\{\hat{\beta}_{it}\} - \hat{\beta}_{it}$. The time trend parameter is found to be of positive yet not significant impact at any level of statistical confidence in the model in which heteroscedasticity was assumed to be present only in $\mathrm{u_{it}}$. The same analysis applies to the stochastic frontier *model (4)* which includes the double heteroscedasticity assumption following the Hadri (1999) and Hadri et al. (2003) approach and its extension for panel data. This is where the time trend was also found to be statistically insignificant and of positive effects on efficiency. It is also shown in Table 2 that the null hypothesis is accepted via the likelihood ratio test at 95% in this *model (4).*

In *model (3)* intermediate inputs were factored in as a third input in the frontier production function. It can be observed that the value of the capital input coefficient is not hugely different from its value in the two-input model presented in *models (1) and (2)*. Whereas the labour input parameter is lower than in *model (1)* when the extra input of intermediates is integrated in *model (3).* However, the extra production input of intermediates was not found to be of a significant importance in the single-heteroscedasticity H_U model.

On the other hand, still the time trend (*T*) shows no sign of any statistical significance in both models. However, in *model (4)*, the exogenous factors were included as an extra vector of variables to correct for heteroscedasticity in the two-sided error term ($random\ noise$).

The integration of the exogenous variables in the maximum likelihood procedure for the panel data yielded a variation in the values of the parameters estimated in the inefficiency function. See *model (4*). This is where the change in technology indicates positive but rather statistically insignificant impact on the frontier production function in this model.

It can be noticed that the human capital (*college* and *non-college* labour) and *ICT* capital coefficients' weights in the inefficiency functions in *models (1), (2), and (3)* do not change substantially, despite the information technology capital *ICT* parameter does not appear to be statistically significant even when the time trend has been included as an additional variable in the production function in *models (2) and (3)*. Nonetheless, in *model (4)* the impact of human capital represented by the *college* labour remains statistically significant and positively associated with higher levels of efficiency. Whereas the *non-college* workers component is still contributing in a negative way to the efficiency.

In terms of the effects of both college and non-college labour inputs on productive efficiency, there seems to be no considerable differences between the two models (the single-heteroscedasticity H_U model and the double-heteroscedasticity H_{UV} model) both presented in *models (3) and (4).* In addition, there seems to be no marked disparity in the weights of the coefficients associated with each factor (college and non-college labour inputs).

In the double-heteroscedasticity three-input *model (4)*, the weights of the parameters of capital, labour differed from their values in *models (1, 2, and 3).* This might be ascribed to the substitutability between production inputs. This is where introducing more intermediate inputs such as energy and materials, less capital and more labour will be required. That is, the use of extra intermediate inputs might imply a reduction in the capital inputs and increase in labour inputs to generate the same volume of output.

Conclusion

By way of summary, the different efficiency models presented in this paper whether in the presence of heteroscedasticity in the one-sided error term or in the symmetric two-sided error term demonstrated the importance of *College* labour (those workers with tertiary education) in enhancing efficiency and productivity at the industry level in the manufacturing sector in the U.S. economy.

It is also proved that the Information and telecommunication *ICT* capital has played a key role in promoting industry efficiency in the U.S. over the period from 1998 to 2019 thanks to the information revolution and the stream of innovations and new technologies in the mid-1990s and its continuous spillovers over the two decades that followed. Regarding the *Non-college* labour (those workers with high school education), the role of this component of human capital in reducing inefficiency at industry level does not seem to be key in the U.S. In fact, in some models it is found to have had negative contributions to efficiency. As for the *R&D* capital, it showed no significant impact on efficiency when included as an endogenous factor in the H_U inefficiency *models 1, 2, and 3,* but when included as an exogenous input in the final H_{UV} *model 4,* it appeared to have had significant effects on efficiency in the U.S. manufacturing sector over the stated period from 1998 to 2019.

The selected sample in this paper is formed of industries with different levels of technology ranging from low and med low technology industries to high and med high technology industries. These industries will – in one way or another – have inter and intra-industries trade links, which by extension will stimulate innovation and technological diffusion among industries. In addition, intra-industry trade in vertically differentiated goods which are recognised by their variety in quality and prices can reflect some endowments in production factors between industries such as highly skilled labour. Hence, trading in these types of markets can offer some industries the opportunity to specialise and direct their resources and trading in the goods that they have some sort of comparative advantages in their production cost, such as using expensive educated workers for research and development and knowledge creation activities while allocating less skilled labour in less complex production activities.

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