

ESSAYS ON THE EFFICIENCY OF SCHOOL EDUCATION



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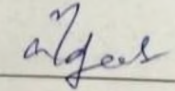
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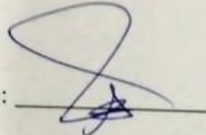
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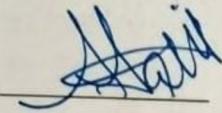
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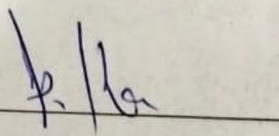
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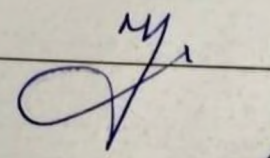
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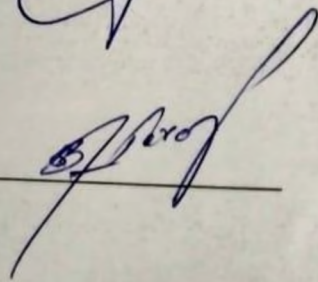
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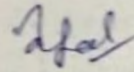
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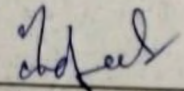
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ABSTRACT

Access to quality education is the intellectual right of every child, and it was first acknowledged in December 1948 in the Universal Declaration of Human Rights (UDHR). Further, it was also stated that education until the primary level should be free, but education should also focus on personal development and promote respect for human beings (UDHR Article 26). Recently, Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs) reinforced the importance of education as a universal right regardless of color, language, race, gender, economic condition, and social origin. It is possible to improve the quality of education by efficiently using inputs. The first section provides the model for resource allocation in education. The object of the model is to maximize the school efficiency and student outputs based on the student's level input variables i.e., ability, effort, and resources.

However, the first question is to measure the performance to analyze how much chance of improvement is available. Essay two of the thesis calculated the total factor productivity using the inputs and output at the district and then at the individual school student level and decomposed it into efficiency components. This study implements Data Envelopment Analysis (DEA) using the DPIN software for the analysis. Panel information from 2013 to 2016 of the 112 districts is used for this study. Technical mix, and scale mix efficiency is calculated, and the determinants that can explain the difference in the performance are measured. Results show that the health and education index are the key indicators that can explain the high performance of some districts. At the same time, the living standard shows a negative effort on efficiency.

For analysis at a granular level is performed by considering district Mardan for further analysis. Data of 1330 respondents are collected from the three districts. Data related to student ability (cognitive and non-cognitive life skills), effort level, and financial resources are collected and along with the family level control variables. Data envelopment analysis is used for the analysis; it was found that the average males score is higher in non-cognitive life skills compared to females. Along with other indicator effort levels and financial resources shows a significant positive effect on student performance. The family level indicators play a major role in explaining the performance differences, when the individual student characteristics, family level characters, and school location and type were regressed on the technical efficiency.

The finding of the thesis suggests that the government needs to make allocation decision based on the individual district's needs. Learning environment, health, and living condition of each districts should be considered by the policy makers while making allocation decision.

Policy makers need to do resources planning and initiate a framework to measure efficiency in education sector that will help in managing the resources devoted to education. Results also suggests that by focusing on teaching methods and trainings can help improve the technical efficiency leading to improved student and school performance. In addition, student's performances is improved by improving the non-cognitive skills like self-confidence, self-esteem, social sensitivity, stress management and thus build a great leader for the future.

Keywords: School efficiency, Total Factor Productivity, DEA,

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LIST OF ABBREVIATIONS

DEA	Date Envelopment Analysis
FDH	The Free Disposal Hull
OCT	Optimal Control Theory
SFA	Stochastic Frontier Analysis
TFP	Total Factor Productivity
DMUs	Decision-Making Units
TJPSQ	Teachers' Performance, A Self-Rating Questionnaire
ASER	Annual Status of Education Report
LEAPS	Learning and Achievement in Pakistan Schools
OSME	Output-oriented Scale Mix Efficiency
OTE	Output-oriented Technical Efficiency
OME	Output-oriented Mix Efficiency
ROSE	Residual Output-oriented Scale Efficiency
TFPI	Total Factor Productivity Index
TFPE	Total Factor Productivity Efficiency
NEMIS	National Education Management Information System
AEPM	Academy of Educational Planning and Management
SDPI	Sustainable Development Policy Institute
PSLM	Pakistan Social and Living Standards Measurement Survey
UDHR	Universal Declaration of Human Right
MDGs	Millennium Development Goals

CHAPTER 1

INTRODUCTION

1.1 Introduction

Education is a means by which an individual may rise above his social and economic situation. The contribution of education to economic growth and individual well-being makes it a compelling area of research. Therefore, providing equal learning opportunities has always been of crucial concern in public instruction, particularly in developing nations. However, the public sector in many developing countries faces fundamental resource issues and lower productivity in the education sector (Silva, 2000). To justify more government support and funding, public institutions must be productive and compete for the scarce resources available to the education sector. That is why access to quality education through the allocation of productive resources has become an essential objective of education policy. Policy makers are increasingly motivated to ensure that the resources are managed, organized, and effectively used so that the best educational outcomes can be achieved (Hanushek, 2005, 2011; Krueger, 2003).

Public institutions such as hospitals, colleges, universities, power plants, railway stations and others work for the welfare of people living in different societies. Administration officers, under the direction of decision-makers, continuously monitor the performance of these institutions and the use of resources provided. This study aims to evaluate the education system in Pakistan regarding optimal allocation of resources and educational performance by inspecting all the essential connected particulars with them, whether it is school, students, teachers, administration, and other managerial activities. Institutions where employees carry out their responsibilities with honesty, acquire competence, and follow the principles are the most effective. However, if we see different institutes that are becoming worse day by day are due to unskilled labor forces, mismanagement of resources, may be due to political inference,

by choosing wrong policies or unskilled teachers/ professionals in the field with fake degrees. Thus, these constraints prevent us from improving the quality of education. Therefore, this study focuses on the problems that contribute to the failure of the education system in our country. Therefore, it is first studies that cover the issue like resource allocation and constraints at the grass-root level that play a significant role in educational performance in the state.

In addition to discussing the role of primary factors, many researchers also considered demographic differences such as gender, age of enrolment in primary school, curriculum, geographic boundaries, and others (Makri-Botsari, 2015). Many other studies discussed the achievement rate separately for male and female students. Dreze and Kingdon (2001) and Afridi (2011) found that in rural India, the girls respond more to the free food distributed in school. The monthly attendance rate of girls in lower grades improved, whereas it has an insignificant effect on the enrollment and attendance rate for male students, ultimately that affect the learning outcome. Krueger (1997) observed the class size impact on students on free lunch for those who belong to minorities. Thus, the author finds that minorities are more responsive to changes in class size and have no impact on learning outcomes. Numerous other studies have examined learning outcomes at various income levels in developed and developing countries (Schanzenbach, 2014).

1.2 Issues of the Thesis

Empirical evidences about the role of human capital in facilitating economic growth and social development (Hanushek & Woessmann, 2008) has led to increased attention on education in low-income and developing countries like Pakistan. The policy rationale is that the improving in human capital in these developing countries could help, in the medium-long run grows and sustainably. According to a study by the Organization for Economic Co-operation and Development (OECD, 2007), 30.7 percent of the resources allocated to the education sector

can be reduced in OECD countries. Still, the same level of educational outcome is achieved. On average across OECD countries, expenditure on R&D and ancillary services at the tertiary level represents 32% of all tertiary expenditure on educational institutions per student. Due to the greater expenditures of facilities and equipment in tertiary education, the share of staff remuneration in total current expenditure in non-tertiary education (77%) is higher than in tertiary education (68%) across OECD nations. Among OECD and partner countries, Argentina, Belgium, Denmark, France, Greece, Iceland, and Poland report the highest proportion of current expenditure given to tertiary staff compensation (75 percent or more). Belgium, Colombia, and Greece spent 85 percent or more of their educational budgets on staff compensation at the non-tertiary level, meaning they spent less on other contracted and purchased services like support services (e.g. building maintenance), ancillary services (e.g. meal programmers), and rent for school buildings and other facilities.

As discussed if the government is spending enough resources than are these resources being used efficiently. There are many studies that discuss the resource use efficiency, however, the efficiency of elementary and secondary schools is not analyzed for Pakistan. Moreover, still few researchers analyzed the determinants of school and student level efficiency.. This is the first study that ever discussed the constraints that can individual student and school face due to which they cannot give the maximum output¹. As a result, the primary **first objective** of this thesis is to discuss the resource allocation problem in theoretic model given the constraints at which the efficiency can be maximized. The solved, model provides the optimal level of inputs i.e. ability, effort level, and financial resources that should be used to maximize the outcome given the governmental spending. By achieving this goal, this study provides the decision maker an analysis that will help in resource allocation decision. This model also included the

¹ The outcome in terms of school efficiency is measured through students performance i.e. the marks that obtain in the annual examination.

variables in an analysis that was not tested in previous studies in particular with the schooling system in developing countries like Pakistan.

Like other developing economies, Pakistan has introduced a priority education policy based on which each student should be provided a quality education. Therefore, the **second objective** of this study is to measure the school efficiency at district level and at individual school level. The input efficiency model used in this research emphasizes that the available resources should be utilized in such way that it can improve outcome, given all other things are being equal. By achieving the goal the policy makers can analyze the margin of improvement with the given resources and can further, decide on allocated additional resources to achieve the full efficiency.

With the given level of efficiency, the **third objective** is to identify the determinants of school efficiency and the various environmental factors. At the district level, the difference in the performance can be explained using the demographic factors, including location, number of schools, population density, and other. Whereas, at school level (particularly student performance) individual student characteristics, socioeconomic status and others can determine the school efficiency. Along with these primary objectives, secondary objectives are mentioned in their respective sections.

1.3 Content of the Thesis and Methodology

In the area of education, policymakers don't only have to make decisions regarding the distribution of resources across different states, districts, schools, and classrooms, but we also need to examine to what extent these resources have been used effectively to improve learning. This study is divided into several sections to deal with all aspects of the issues, which are as follows. .

Chapter 2 discusses the issue of optimal allocation of school resources, given the fact that the resources are scarce; it increases the competition between public and private schools for the use of resources. If the resources allocated to public schools are not used effectively, the social planner must reconsider his decision concerning the educational expenses of the school (Antunes & Peeters, 2000). However, public schools face many other constraints that limit their ability to perform well as discussed earlier. So, how can we allocate resources to maximize the efficiency of the school and the level of students with the given constraints? Thus, the main objective of the first essay is to determine the optimal level of resources that should be spend by the government and the optimal level of student's effort that is need to maximize the outcome i.e., student performance in a principal agent simplified model. This theoretical model takes into consideration the cost-benefit analysis when making the optimal decision. Furthermore, we examine the optimal level of ability that students can achieve to maximize their results. Moreover, the analysis also takes into account the constraints faced by schools and students to maximize the outcome in equilibrium.

Further, Chapter 3 investigates the role of school resources in explaining school efficiency at district level. More specifically, it discussed the effective use of available resources that we can maximize the efficiency of schools. In particular, the various goals we intend to achieve with this research are to examine government-spending patterns in education. In addition, calculate efficiencies for each district, taking into account district-controlled variables, and explore the role of resources to improve efficiencies. Efficiency is derived by breaking down total factor productivity into its components. Thus, this helps us in examining which type of resources is necessary to improve efficiency, i.e., human capital or physical resources, or others. Further, two step DEA method is used to investigate the district level factors that can explain the differences in the efficiency level using the Tobit model. In addition, the analysis

carried out as part of this study provides policy makers with guidelines on characteristics at the district level that should also be taken into account when making allocation decisions.

Chapter 4 discusses the student-level constraints that can affect its performance. During his academic years, there are many problems that a student face, including time management, financial issues, quality education, homesickness, stress, health issue, difficulty in learning, communication issues, language barriers, school bullying, the relationship between student, teacher, and guardian, guidance issue, high parental expectations, lack of motivation, transportation, lack of facilities, access, and others. Thus, students' have to deal with both personal problems and the problems in schools; however, overcoming these challenges and managing large workloads is part of the learning process (Fook & Sidhu, 2015). This essay focuses on the student's abilities, time, and resource constraints that he faces in his academic years. The main purpose of this study is to estimate the efficiency score of the student and to examine the determinants of efficiency at the student level. The student's efficiency score is calculated by decomposing the total factor productivity. The Tobit model is then used in the second stage to examine differences in student efficiency scores based on individual student characteristics, family socio-economic status, and location. Finally, the research provides guidelines for developing appropriate educational policies based on the findings of this chapter. Chapter 5 is the last chapter to address the main idea of the proposal. It primarily highlights the significance of the study and discusses the limitations and prospects of the study.

The literature discusses many different approaches to measuring student learning outcomes and academic achievement. However, this study uses the concept of total factor productivity and efficiency of performance measurement. Many domains, discuss the concept of efficiency in measuring performance, including agriculture, banking, and education. Generally, the concept of efficiency is the production process that converts inputs into outputs.

However, the output is efficient if we can produce more without reducing the output of some other production processes. Therefore, if the same level of inputs can produce more outputs without reducing the output of any other production process, it is an ineffective outcome. Hanushek (1986) defines efficiency as the maximum level of outcome for the given number of resources. Therefore, the concept of efficiency relates to the optimal allocation of resources. Hence, economic efficiency is all about making the best use of the scarce resources available between the competing ends to maximize economic and social welfare. Mainly, two types of efficiency models are available in the literature, first is the output efficiency model that refers to the increasing level of output with the same level of inputs. Second is the input efficiency model that can be defined as producing the same level of output with the least input resources. This study focuses on the output oriented efficiency model by O'Donnell, (2008) which is a linear programming model under the framework of Data Envelopment Model. The efficiency level in this method is obtained by decomposing the TFP index into different components of technological, technical, scale and scope efficiency change.

Unlike statistical approaches, DEA is capable of supporting multiple inputs and outputs. Like any performance measurement technique, DEA has advantages as well as disadvantages. This is a strength in the context of the public sector where many non-monetary outputs are usually provided. However, the specification (i.e. selection and/or quantity) of inputs and outputs to be included in the analysis affects efficiency outcomes. Exclusion of significant inputs or outputs may bias outcomes Cooper et al. (2006). Multicollinearity associated with a large number of inflows or outflows has long been under-studied in the DEA (Johnes, 2004, p. 643), but does not appear to be a problem (Smith, 2005). Endogeneity, on the other hand, has implications for DEA, even though DEA does not model the relations between inputs and outputs. Smith (2006) discusses whether input levels can be endogenous when feedback occurs between outputs and inputs assigned to the activity. They show that endogeneity can lead to

biased efficacy results with small sample sizes. However, the bias is smaller as the sample size increases. Further, the advantage is, therefore, that no econometric assumptions are required and no uncertainties in the TFP change, i.e., no error term. Specifically, no error term avoids statistical concerns such as endogeneity (see, e.g., O'Donnell, 2012).

The contributions from this dissertation enrich the literature both methodologically and empirically. The implications of the thesis are broad in the sense that each essay is examined at different levels. Furthermore, some policy implications can be drawn based on the conclusions; however, notes are also provided in areas that are not considered but left for future research in the concluding chapter.

CHAPTER 2

ESSAY 1: OPTIMAL ALLOCATION OF SCHOOL RESOURCES

2.1 Introduction

Substantially, the ongoing debate on educational reforms deals with the issue of resource management. The policymakers are motivated by the desire that the resources that are allocated in education are managed, organized, and used effectively so that the schools' efficiency and student's outcome is maximized. Specifically, the linkage between the additional resources and improved education is contentious; thus, without enough evidence, researchers are interested in exploring alternative ways of improving the educational outcome (Hanushek, 2006; Krueger, 2003). Thus, researchers focus more on how a particular resource can be used effectively to improve outcomes.

The existing literature in education tries to explore the allocation and resource mix at different levels. In particular, the education system is divided into three basic types, first the public school system supported by the government and administered by the local authorities. Second, there are some schools with public-private partnerships that are administered by a private contractor, but receive partial funding from the government. Third, there are private schools that receive no government funding and are managed only by a private contractor. There are schools run by religious authorities.

Moreover, based on the resources available, in the three education systems, student performance is the indicator of school quality. However, the education sector is dominated by public schools around the globe. Furthermore, it is assumed that public schools do not receive sufficient incentives to improve student performance and thus fail to use allocated resources effectively. This means that low-performing public schools is subject to high social costs. While, because of the competitive environment in the private sector, they seek to maximize

performance to stay in the marketplace (Bishop & Wobmann, 2004). Thus, the private education system strives to maximize its benefits and has an incentive to utilize their resources effectively. Some researchers are of the view that the role of public schooling is not to maximize performance, instead, to provide education to all, maximum benefit to society, minimize cost and equity (Antunes & Peeters, 2000; C. M. Hoxby & Ladd, 2003). However, the achievement of objectives is subject to many constraints like budget, capacity, human resources, watershed constraints (time required to reach school/distance), and others.

So, in this situation, the problem faced by the social planner is to decide about the schools that should remain open and which should be closed based on their performance and where new schools should be opened based on demand in any particular area. Furthermore, for public schools that remain open, if they are to be resized and what impact these decisions have on short- and long-term educational demand (Antunes & Peeters, 2000).

The emphasis of many previous studies is on the number of resources to be allocated in the education sector, i.e., for infrastructure, human resources, and learning opportunities. Whereas, recent research focuses more on the efficient allocation of resources, i.e., how can the available resources be used to maximize the efficiency of the educational production function (Cobb-Clark & Jha, 2016; Matter, Shiotani, & Hendges, 2009; Sallee, Resch, & Courant, 2008; Silva, 2000). Therefore, provide more space for social planners on how to effectively distribute and manage learning and teaching resources. The social planner is not only concerned about how resources are allocated, but also about their distribution among districts (rural and urban), schools, and students. In addition, how these resources enhance learning opportunities, help fill existing gaps and achieve the target (Plecki & Castanedo, 2009).

2.1.1 Objectives of the Study

The purpose of this study is to determine the optimal level of resources that will maximize efficiencies at the societal level. Further, it will determine the individual student net benefit based on its educational outcome of considering the school level resources (allocated to each school by social planner), parental resources provided, and the student's related attributes. Thus, the first objective function of this model is to maximize the student outcome, and the second objective function is to maximize the educational outcomes at the school level, representing the Governmental level net benefit both at the same time.

Primary Purpose:

- To determine the optimal level of resources that maximizes the Outcome.

Secondary Purposes:

- Investigate the optimal number of resources that should be allocated to each school.
- Investigate the optimal level of ability and the effort level that each student requires to maximize its outcome and
- Identify the constraints faced by schools and students in maximizing output and efficiency

2.1.2 Significance of the Study

In most developing countries, even if the funds are available and invested efficiently, majority school cannot be maximized its performance, as many constraints limit them from giving its best performance. This study helps implement a systematic approach that can solve problems at multiple levels, and resources are allocated to maximize welfare. Thus, this study helps the social planner to decide on the optimal amount of input resources that are to be allocated to

each school given the student population, average students' abilities in each school, its operating cost, and location, i.e., rural or urban. This is the one of the first theoretical model of education production that considered the cost and benefit analysis for the government spending decision. The principle agent framework where government decide for the resource allocation, current model in additional considers the constraints that educational institutions face in improving their performance. Even though the empirical testing of the theoretical model is not covered in this study. However, the simulated results can help the resource allocator in analyzing the magnitude of change, the ability, effort and resource can have on the student and school outcomes.

2.2 Literature Review

Taking into account rising birth rates in growing economies, the demand for educated and skilled labor has also increased. Thus, to meet the increasing demand for educational services, resources are needed. An extensive set of literature guides us on who the budgetary allocations can be made and how the optimality can be achieved. Therefore, to make resource allocation related decisions, it is essential to know the number of institutions, the student population at different levels, and geographical location of institution and hence the number of resources needed to produce an adequate level of outcome. As a result, different approaches exist to model efficiency and predict the level of resources required. Historically, not many researchers were interested in the number of students across different levels and their projections (J. Johnes, Portela, & Thanassoulis, 2017). Thus, based on this information, the model is made to predict the number of teachers, administrative staff, and equipment required across each educational level (Lee & Moore, 1974). There are different mathematical models used in education planning which have used the flow of different mathematical relations to make budget decisions; however, these models differ in their mathematical representation.

The literature extensively discusses models that address optimization, precisely the optimal solution in public planning. Social planners use these optimization models across a wide spectrum of decision-making, including education. More specifically, the models in education deal with the optimality in the use of resources and provide the optimal solution to the problems faced by the planners. *Leontief input-output model*, *Simulation*, and *Markov Chain Method* are used to model resources required for students across different levels and time. However, the mathematical models should provide the answer to the optimality that is required by the policymakers. Besides the expected student population and the necessary resources, the funding decision is also crucial for decision makers.

Linear programming plays an important role in efficiency analysis. Charnes, Cooper and Rhodes, (1978, 1979) was amongst the first one who developed the linear programming and used it in the application of Data Envelopment Analysis (DEA) modeling. Leontief (1953), the efficiency and productivity input-output model is closely linked to work by Koopmans (1951) (Shephard, 1970) and (Afridi, 2011) on production programming models. These programming models related the input and output values, making a pairwise linear frontier production model. While implementing the programming models in microeconomics, Koopmans and Shephard restricted convexity, which was then relaxed by the (Deprins, 1984), introducing the new estimation technique called “The Free Disposal Hull” (FDH). Therefore, programming models help in revealing the frontier, without imposing any functional form of the data (non-parametric model). Linear programming models are also applied to the production models (parametric model) where the functional form is known, i.e., Cobb Douglas in many cases (Bishop & Wößmann, 2010; Bratti & Staffolani, 2002; K Chakraborty, Biswas, & Lewis, 2001; Dolton, Marcenaro, & Navarro, 2003; Ghose, 2017; Sallee et al., 2008).

Because several objects must be realized, therefore the government must allocate resources to a state district in a way to achieve multiple objectives, Roy (1971), Cobacho *et al.*

(2010), and others suggested the use of *Goal Programming* to make a decision. Fandel and Gal (2001), Sinuany-Stern (1984), Hopkins and Massy (1977), and many other studies used goal programming for allocating budgets. At the organizational level, Lee and Clayton (1972) and Geoffrion *et al.* (1972) used goal programming models to allocate organizational resources amongst different departments and time allocation of staff amongst different activities like research, teaching, and administration, respectively. Another study by Finlay and Gregory (1994) discusses the role of the resource management system in time allocation between four different activities, i.e. administration, teaching, research, and supervision. However, the emphasis should not be solely on equal time allocation, but rather on time allocation based on the needs and nature of the activity. Although the primary objective of the attribution activity is to maximize output. Optimal Control Theory (OCT) is also used to solve the optimality problem at the national level for the school resource distribution (Dhaene *et al.*, 2012; Wan & Zhou, 2011; Hartl, 1983). A similar approach is used to solve the optimal education decisions for an individual (Pantelous & Kalogeropoulos, 2009). However, these models are complex and difficult to implement. A simplified version of a complex model can help get a practical solution to the allocation problem.

However, the decision to allocate education resources is complicated, as many interest groups are involved, as well as multiple goals that are socially optimal and should be met. In addition, it is difficult to evaluate the costs and benefits associated with the alternative use of resources. Different criteria for the allocation of resources in education are spatial allocation specifically based on the location (urban, rural), size, number of schools, time and cost needed to travel to the nearest school, district type (Amaya, Peeters, Uribe, & Valenzuela, 2016; Malczewski & Jackson, 2000). Other studies consider geographical space as the state, province, or region. Thus, each unit of school may vary in its socioeconomic status, demographics, lifestyles, and others due to which the cost of providing education (quality and quantity) may

vary across these units. Thus, this provides evidence that to achieve equal levels of the outcome, the level of inputs (resources) may vary across these units because of the differences in school and district characteristics (Cobb-Clark & Jha, 2016; Rubenstein, Schwartz, Stiefel, & Amor, 2007). There are many criteria in the literature that directs us how optimality can be achieved. However, these approaches must consider stakeholder interests, be socially acceptable, and take into account objectives that are vital to decision-makers.

Therefore, principal agent models are applied in a simplified framework, to obtain the optimal level of student ability, effort, and governmental resource. Additionally, the Cobb-Douglas production function is applied to ease the representation of the model. The model thus developed helps to analyze the impact of the effect of the location on the overall outcome at the school level. Hence, this model can be extended to make a resource allocation decision across schools based on the student population and the number of schools within each district.

2.3 The Model

The literature reviewed emphasized that the research in the area of education is not established based on any theoretical modeling, due to which it is difficult to conclude how the resource allocation might affect the efficiency and educational outcome. However, (Blatchford & Mortimore, 1994) stress the importance of modeling based on some theoretical background, which is derived from research, teaching, and learning process. Many studies generally assume that resources applied to school or pupil play an essential role in improving the efficiency of an educational institution, hence produce better learning outcome (Hanushek, Rivkin, & Taylor, 1996; Ortiz, Johnson, & Johnson, 1996; One & Saito, 2007; Chen, Huang, & Huang, 2009; Huuki, Manninen, & Sunnari, 2010; J. Roy, 2011; Theriot & Orme, 2014). Thus, to study the relationship between resource allocation, effectiveness and student performance, a black box approach is used. Few studies guide model specification for empirical analysis, however majority studies in the area of education are not based on any such model due to which this

field faces the problem of omitted variable biased (Creemers & Reezigt, 1999; Reezigt & Creemers, 2005; Smetana, 2006). This study aims to fill the gap in this field by providing a model for resource allocation along with the constraints that educational institutions face in improving their performance.

The social planner aims to model the efficiency of the schools and the outcome given the educational production function. The social planner is confronted with the problem of allocating resources among schools based on their performance. Furthermore, the planner models the educational outcome of the students. The planner decides on the allocation of resources and the optimal number of schools in society, taking into account the distribution function of the students, their location, and the operating costs of a school. The resources available to the planner are mainly from four sources, i.e., human resources, financial resources, physical resources, and funding for targeted programs. The total educational resources available to social planners are spent on either in school or on students (Pons et al., 2015). Thus, the social planner does not only care about the distribution of resources, but also focuses on the use and management of resources.

Considering the utilitarian welfare function, planners want to maximize the overall outcome of society's education. Thus, we model the multiple objectives of the planner simultaneously. Student outcomes in the model are dependent on school-level resources, family-level resources, and individual efforts. The outcome is demonstrated based on the ability, effort level, and resource they receive. Students have to face budget and time constraints. The total financial resources available to students are from two sources, i.e., share of school resources and share of family income spent on individual students. Further, the student spent the total time available in attending classes, learning at home (self-study), and other activities. For the simplicity of the model, students are considered homogeneous.

Assumptions of the model are as follows:

1. This model considers the finite set of student population in targeted area $S = \{s_1, \dots, s_i\}$.
2. Set of a finite number of schools $K = \{k_1, \dots, k\}$
3. Teacher population is represented as $J = \{j_1, \dots, j\}$
4. Student abilities are considered homogenous at the aggregate school level, whereas heterogeneous within school, i.e., each student has a different level of abilities. We assumed that there are no unobserved characteristics between students in the class that affect the achievement level.
5. The educational production function is assumed to have a decreasing return to scale.
6. To maximize allocative efficiency, school has to face three different constraints related to financial recourse, human resources, and time constraints. Likewise, to maximize the outcome, individual students have to face a similar constraint.
7. There is a fixed operating cost for establishing a school
8. Distribution of students is assumed normal across the district/state.
9. It is assumed that education production is concave.
10. This claim numerically, assuming that ability is distributed uniformly on $[0; 1]$.

The educational production function can be simplified through the Cobb-Douglas production function. It will be relatively easy to conclude the model and results can be interpreted using this functional form. School efficiency is measured by “Q”, which is the reflection of the student’s outcome. In terms of individual student, the outcome is the marks./score obtained in the annual examination. This research focused on is the educational outcome; input variables include the resources available to the student, i.e., teachers, opportunities, scholarships, and the effectiveness of the use of resources. Resource effectiveness also includes the teaching methods, assessment methods and amount of

information that should be available to students and their parents to make educational decisions. Ability is also used as an input factor with includes not only the student's cognitive skills but also the family-related attributes, other factors such as neighborhoods, peers, or general institutional structure are combined with the effort the students, motivation and time invested, which is the stochastic element of the individual student.

$$Q_s = f(A_s, E_s, R_s) \quad (2.1)$$

$$Q = A^\alpha E^\beta R^\gamma \quad (2.2)$$

$$0 < \alpha, \beta, \gamma < 1, \quad \alpha > 1, \quad \beta > 1, \quad \gamma > 1, \quad \alpha + \beta + \gamma < 1$$

In the above equation Q represents the educational outcome of student (annual marks), R are the total available resources, A is the student learning ability and E is the effort level, i.e., the number of hours he spends studying out of school. Overall, three inputs are combined to make up the production process. The ability, effort level and the available resources. The students are assumed homogenous in this model; therefore, the subscripts are omitted. α , β and γ parameters represents the elasticity of student performance with respect to inputs. Therefore, a positive interaction is ensured in Cobb Douglas' functional form. It would be realistic to assume that a proportional increase in the student's ability, effort level, and resources will be less than one, i.e. less than propitiate in the student outcome².

Overall, learning ability is dependent on both the student's ability to learn and the teacher's ability to teach. In addition, it is the inherited ability, the learning environment, and the learning experience over time. Overall, it can be said that all the effects combine to determine the overall students' readiness at school. Thus, the student's ability can be represented as follows

² Here $\alpha + \beta + \gamma < 1$ is a sufficient condition, not the necessary one, as it is more specific that what is needed.

Student's Abilities

$$\sum_{s=1}^S A_s = \sum_{s=1}^S (\theta_0 \mathbf{Class}A_s + \theta_1 \mathbf{Math}A_s + \theta_2 \mathbf{Native}A_s + \theta_3 \mathbf{OutSch}A_s) \quad (2.3)$$

Teacher's Abilities

$$\sum_{j=1}^J TA_j = \sum_{j=1}^J (\beta_0 \mathbf{TEdu}_j + \beta_1 \mathbf{TSlry}_j + \beta_2 \mathbf{TExp}_j + \beta_3 \mathbf{TAvb}_j) \quad (2.4)$$

Where, A_s is the ability of the s^{th} student. Many studies in the literature show that the students learning abilities depend on different factors, some are classroom learning abilities (affective learning skills), mathematics learning skills (ability to pick a number sequence), out of school learning (psychomotor skills) and native abilities (cognitive). The abilities of the j^{th} teacher available to s^{th} student. A teacher's ability is considered as a function of its education, salary, teaching experience, and the number of hours he is available. Ability constraints are based on the assumption that it is uniformly distributed between the interval $[0, 1]$.

Student effort level is the most important input that is controlled by the student himself. It represents the level of motivation, engagement and the time he is spending on learning. The number of hours spending on learning by a student and the number of hours spend with a teacher in teaching is reflected in the student performance.

- Students Effort level

$$\omega_0 t_{us} + \omega_1 t_{vs} + \omega_2 t_{cs} = T \quad (2.5)$$

$$E_s = \omega_1 t_{vs} = T - \omega_2 t_{cs} - \omega_0 t_{us} \quad (2.6)$$

$$T \leq 24 \quad t_{us} \leq 8, \quad t_{vs} \leq 4, \quad t_{cs} \leq 12$$

Where T is the constrain on the total time available for s^{th} student, t_{us} is the time spent on learning in school, t_{vs} is the number of hours spent on learning after school (effort level, E_s) and t_{cs} is the time spent on other activities (Bratti & Staffolani, 2002).

- Teachers Effort Level

$$\delta_0 t_{uj} + \delta_1 t_{vj} + \delta_2 t_{cj} = T \quad (2.7)$$

$$E_t = \delta_0 t_{uj} = T - \delta_1 t_{vj} - \delta_2 t_{cj} \quad (2.8)$$

$$T \leq 24, \quad t_{uj} \leq 8, \quad t_{vj} \leq 24, \quad t_{cj} \leq 24$$

Further, time constrain faced by j^{th} teacher, t_{uj} is the number of hours spent teaching at school (also referred to as the teacher effort, E_t), t_{vj} is the time provided to some students for extra tuition and rest is the time spent for other daily activities, denoted by t_{cj} .

Total resources are represented by the term, R , which shows the number of resources that go into the learning process. It is not necessary that the total educational expenditure X in the schooling system is equal to the R , rather the spending could be on other objectives as well like scholarship to students and development. Therefore, $(1-d) X$ is the amount of government resources invested in education. The parameter “ d ” represents the number of resources that are diverted from teachers, thus a value of $d = 1$ thus represents that any further increase in educational resources will have any impact on the performance of students. Thus, for the effective use of resources, the school’s management plays a role in preventing the misuse of school and administrative funds, further allocation of the teacher’s time towards not productive activities.

Hence governmental resource towards teaching, number of resources that a family spends for the child school education (m_s) and student scholarships (r_s) combines together to define the total available resources R .

$$R = (1-d) X + M \quad (2.9)$$

The family resources that students use to learn are:

$$M = r_s + m_s \quad (2.10)$$

$$r_s = (\rho_s F) / S$$

$$m_s = (\sigma_s I) / n$$

$$\rho_s \leq 1$$

$$m_s \leq 1$$

Where, M is defined as the total financial resources available to s^{th} student and are determined outside the system. The proportion of Financial resources (F) from governmental and non-governmental resources spend on s^{th} student is defined by r_s in terms of scholarship and S is the total number of students. Proportion of Family resources (I) spend on s^{th} students are indicated by m_s . Whereas, “I” is the total family income earned and n is the family size (number of dependents on the family income). Total available resource to a student is used to cover the expenditures of individual students are divided and categorized as school fees, books/copies and stationary expense, the cost of the uniform, extra tuition fee, and other miscellaneous expenses. The proportion of financial resources that a student received from a family is too small as compared to the governmental, educational spending in the public sector, therefore to simply the model it is assumed zero.

2.3.1 Student Outcome Maximization

The two main shake holds in the model are the social planner and the student who wants to maximize their net benefit. Student attitude, lifelong learning, and the teacher's ability to teach will determine the maximum benefit to the student. However, the resources

received by the student are under the control of the social planner, hence exogenous to the student. Thus, the student benefit is as follows

$$B_s = wQ = wA^\alpha E^\beta R^\gamma \quad (2.11)$$

Where w stands for the overall reward of learning that is received by the student in terms of higher income, social status, honor and respect that he will receive in the future. The student outcome may also guarantee the future earning along with the effort he puts starting from the start of the admission until the time the student completes his studies and become part of the labor market. The student cost function is as follows.

$$C_s = cE^\mu + aA^\vartheta \quad (2.12)$$

$$\mu > 1, \vartheta > 1$$

Where c and a are the constants. The cost combines the opportunity cost of student time (E^μ) and students' inability to study (A^ϑ). Specifically, the inability to manage in-class study time, any extra time required for learning activities such as tuition and travel time. In addition, peer pressure also affects the time that can be effectively used for learning. The elasticity " μ " represents the students time cost with respects to effort level is greater than one i.e., any additional time taken away from the leisure activities and spent of learning is an increasing cost.

To determine the optimal level of student effort, we will consider maximizing the net benefit of the student with a given level of government spending and ability.

$$S: \max_E (B_s - C_s)$$

$$\Rightarrow \frac{\partial(B_s - C_s)}{\partial E} = w\beta A^\alpha E^{\beta-1} R^\gamma - c\mu E^{\mu-1} = 0 \quad (2.13)$$

Solving the above equation will yield the optimal level of effort that a student should choose to maximize their outcome:

$$E = \left[\frac{\beta}{\mu c} w A^\alpha ((1-d)X)^\gamma \right]^{\frac{1}{\mu-\beta}} \quad (2.14)$$

Similarly, the Student's inability to study is a cost that represents its failure to learn in class (cognitive skill), which can also be associated with the lack of qualified teachers and their skills to teach. Further, the inability of a student to cope up with the school work pressure, control over the psychic energy level of the learning, lack of focus and self-confident can also affect the students' performance. Thus, elasticity " ϑ " represents the cost with respect to ability and is assumed to be greater than one, as the marginal cost increases as the inability increases. Thus, the student chooses to maximize his benefit, which is shown as:

$$S: \max_A (B_s - C_s)$$

$$\frac{\partial (B_s - C_s)}{\partial A} = w \alpha A^{\alpha-1} E^\beta R^\gamma - \alpha v A^{\vartheta-1} = 0 \quad (2.15)$$

Thus, the optimal level of student ability with a given level of government spending (X) and the chosen level of effort is shown in the equation below.

$$A = \left[\frac{\alpha}{\vartheta v} w E^\beta ((1-d)X)^\gamma \right]^{\frac{1}{\vartheta-\alpha}} \quad (2.16)$$

2.3.2 School level Outcome Maximization

To determine the governmental level of spending that will maximize the school efficiency, this section will consider the government level benefits (B_G), which is measured as the learning reward of the individual student (wQ) and the general public weighted by parameter P . For the

purpose of simplicity, the model assumes that there are not external benefits attached to the education. In addition, the preference of the government to improve the academic standards and prioritize the teacher training and development is represented by the higher weight assigned to P . The government cost for the educational spending for the school resources is represented by C_G .

$$B_G = PwQ = PwA^\alpha E^\beta R^\gamma \quad (2.17)$$

$$C_G = X \quad (2.18)$$

The optimal level of governmental spending can be achieved by maximizing the net benefit of the governmental educational expenditures.

$$G: \max_X (B_s - C_s)$$

$$\frac{\partial(B_G - C_G)}{\partial X} = Pw\gamma A^\alpha E^\beta (1 - d)^\gamma X^{\gamma-1} - 1 = 0 \quad (2.19)$$

The optimal level of governmental spending given the Ability and effort level is determined as below:

$$X = [\gamma PwA^\alpha E^\beta (1 - d)^\gamma]^{\frac{1}{1-\gamma}} \quad (2.20)$$

Thus, it can be seen from the equation (2.20) that the overall spending X is in the control of the government and not the R and M . Thus, the governmental level of spending is chosen given the student's ability and effort level in the institutional setting.

2.4 Solution to the Problem

The problem of resource allocation is formulated in the last section. The basic idea is to formulate the structure of the problem and propose a possible solution. The optimal level of effort level, ability, and government spending are obtained in equation 2.14, 2.16, and 2.20.

System of simultaneous equation is solved to get the equilibrium value of A, E and X, where the net benefit of individual students and government is maximized. Equations 2.14, 2.16 and 2.20, are solved in pairs to get the model solution. Thus, my solving the first pair of equation 2.14 and 2.16, the student effort level given the level of governmental spending is obtained as:

$$E = \left[\frac{\beta^{(\vartheta-\alpha)}}{\mu c} \frac{\alpha w \alpha}{\vartheta a} ((1-d)X)^{\gamma \vartheta} \right]^{\frac{1}{\Delta 1}} \quad (2.21)$$

$$\text{Where } \Delta 1 = \mu \vartheta - \mu \alpha - \beta \vartheta$$

Similarly, the second pair of equation 2.16 and 2.20 is solved to get the spending level X with the given effort level E given as:

$$X = \left[\gamma P w^{(\vartheta-\alpha)} \frac{\alpha w^{(1-\gamma)}}{\vartheta a} E^{\beta} (1-d)^{\gamma} \right]^{\frac{1}{\Delta 2}} \quad (2.22)$$

$$\Delta 2 = \vartheta - \alpha - \vartheta \gamma$$

Solving equation 2.21 and 2.22 will yields the equilibrium value of E, A and X. Student level effort is represented as

$$E^* = \left[\frac{\beta^{(\vartheta-\alpha)(\Delta 3+\beta \gamma \vartheta)}}{\mu c} \frac{\alpha w^{(\Delta 3 \alpha+\Delta 1 \gamma \vartheta-\Delta 1 \gamma^2 \vartheta+\alpha \beta \gamma \vartheta)}}{\vartheta a} (\gamma P w)^{(\vartheta-\gamma) \gamma \vartheta \Delta 1} (1-d)^{(\Delta 3 \gamma \vartheta+\gamma^2 \vartheta \Delta 1+\gamma^2 \vartheta^2 \beta)} \right]^{\frac{1}{\Delta 1 \Delta 3}} \quad (2.23)$$

$$\Delta 3 = (\mu \vartheta - \mu \alpha - \beta \vartheta)(\vartheta - \alpha - \vartheta \gamma) - \gamma \vartheta \beta$$

The above equation shows that the student effort level is positively affected by the lifelong learning award w and the interest of government to improve academic standard P . Whereas, it is negatively affected by the cost of effort, inability to study and the amount of spending diverted from the overall spending.

The student Ability level at the equilibrium is represented as:

$$A = \left[\frac{\alpha}{\vartheta a} w ((1-d)X)^{\gamma} \right]^{\frac{1}{\vartheta-\alpha}}$$

$$\left[\frac{\beta^{(\vartheta-\alpha)(\Delta 3+\beta \gamma \vartheta)}}{\mu c} \frac{\alpha w^{(\Delta 3 \alpha+\Delta 1 \gamma \vartheta-\Delta 1 \gamma^2 \vartheta+\alpha \beta \gamma \vartheta)}}{\vartheta a} (\gamma P w)^{(\vartheta-\gamma) \gamma \vartheta \Delta 1} (1-d)^{(\Delta 3 \gamma \vartheta+\gamma^2 \vartheta \Delta 1+\gamma^2 \vartheta^2 \beta)} \right]^{\frac{1}{\Delta 1 \Delta 3}}$$

$$d)^{(\Delta 3\gamma\vartheta + \gamma^2\vartheta\Delta 1 + \gamma^2\vartheta^2\beta)} \left] \frac{1}{\Delta 1\Delta 3} \frac{\beta}{\vartheta - \alpha} \left[(\gamma P W)^{(\vartheta - \gamma)\Delta 1} \frac{\beta}{\mu c} \frac{(\vartheta - \alpha)\beta}{\vartheta a} \frac{\alpha w^{(\Delta 1 - \Delta 1\gamma + \alpha\beta)}}{\vartheta a} (1 - d)^{(\gamma\Delta 1 + \gamma\vartheta\beta)} \right] \frac{1}{\Delta 3} \frac{\gamma}{(\vartheta - \alpha)} \quad (2.24)$$

The governmental spending at the equilibrium level is given as

$$X = \left[(\gamma P W)^{(\vartheta - \gamma)\Delta 1} \frac{\beta}{\mu c} \frac{(\vartheta - \alpha)\beta}{\vartheta a} \frac{\alpha w^{(\Delta 1 - \Delta 1\gamma + \alpha\beta)}}{\vartheta a} (1 - d)^{(\gamma\Delta 1 + \gamma\vartheta\beta)} \right] \frac{1}{\Delta 3} \quad (2.25)$$

Equation 2.24 and 2.25 shows that the same positive impact of w and P and the negative effect can be observed for the cost of effort, ability and diverted spending. However, elasticities may respond differently for these parameters. It can be seen that different parameters combine together in the production function to yield the student outcome parameter Q . Further, the results solely depend on the value of the parameters $\alpha, \beta, \gamma, \mu$ and ϑ .

In the model discussed about the ability is considered as the combined effect of the student's ability to learn and the teacher's ability to teach. Similarly, the level of effort represents the student effort/time spent on learning activities, in addition to the time spent by the teacher to teach. The extension of this model can also be a disaggregated analysis of the effect at the student and teacher level that can help us analyze the dominant factor. As a result, disaggregated analysis can help the social planner determine the optimum level of teacher effort that can maximize the net benefit. Similar model has been solved by Ejsmont, W. (2009) who discuss the role of teacher quality by can make an effort on student performance. Moreover, in the absence of consistent evidence that increasing educational resources can improve student achievement, researchers continue to find another way to improve student achievement. Therefore, the way institutions are organized, managed and monitored can also be linked with the student performed/outcome (Bishop & Wobmann, 2004, Jean-Marc, 2014).

In general, different social, economic and environmental factors like location, number of schools in the same locality, student population, administrative control, teacher's quality and

ability to teach, parental influence and others are assumed to have a positive effect on the student performance and school level outcome. However, in contracts when there are many stakeholders involved in the decision-making process it can adversely affect the academic quality. Consider the case when the teachers are allowed to make unions, and can affect the teaching workload, then it can be expected to have a negative effect.

2.5 Conclusion

The model discussed in this paper provides the decision-maker with information on the level of expenditure decisions. With the given level of resources, the maximum level of outcome that can be achieved can therefore be calculated empirically from the parameter values.

This paper addresses the major resource allocation issue. A Cobb, Douglas production function is used to simplify the model and get the optimal level of input resources needed to maximize the student outcome. The model also shows different constraints that an individual student and a government institution have to face while discussing production maximization. Thus, the student and the government institution want to maximize their net benefit, given the ability, effort and resource constraints they face.

The empirical solution of the above-mentioned model may be solved by finding the values of all the parameters used in the model. The values of the parameters can be decided by using the historical data series. Furthermore, the parameter values to be used in the empirical model can be an interesting area of discussion with different policy makers and researchers working in the field. Also, derive the guidance from similar models developed in the literature. However, in case of education data for Pakistan have limitation due to which we cannot find the historical data that can guide us to choose the value of the parameters used. However, there are both merits and demerits of this methodology. Thus, this technique is more flexible and allows us to experiment with different parametric values to get the optimal solution. However,

the demerit is the lack of consistent methodology in calculating the parameter values as different techniques use to estimate a wide range of parameters.

A more comprehensive modelling of the educational production function is to be performed by reducing restrictions on students and government. Disaggregated analysis of the simple model can help policy makers make a more objective oriented decision. Further, it will help with analysis either it's the student side of the institutional size that need improvement. A minimum threshold level of abilities and effort level that should be attained by the student should be identified by using the outcome based educational methodology, so that no student is left behind. Likewise, the minimum level of competence of the teacher should be checked and, if further training or further training is requested, the administration should take the necessary measures. A more flexible model should motivate to include other stakeholder than the one discussed in this model like teachers and parents, that maximizes their own net benefit based on their choice variables. Another, extension of the model can be the situation where government spending is not endogenous and resource allocation is not based on optimality. In addition, this paper explains that, instead of increasing expenditures, resources should be used efficiently to improve the quality of studies. Therefore, administrative role in the institutional set is much more promising to achieve the desired results.

CHAPTER 3

ESSAY 2: DECOMPOSITION OF TOTAL FACTOR PRODUCTIVITY INTO EFFICIENCY COMPONENTS: AN EMPIRICAL ANALYSIS OF DISTRICT LEVEL SCHOOL PERFORMANCE

3.1 Introduction

Education plays a significant role in growth and development. Education provides people with the knowledge, skills, and equal opportunities that they require to make a decent living (World Bank, 2011). As per Sustainable Development Goals 2030 (SDGs) each country is trying to update education system and achieve the development goals.

One of the main goals of institutional economics is to analyze the performance of educational institution because it is the baseline and fundamental unit, which can create change in the development process. Since some time, Pakistan has been struggling to provide quality education across to country to school aged children .The progress of the education sector over the past decade is extremely below desired levels, with a low literacy rate of 58 percent, as reported by the Pakistan economic Survey (2017-18). Pakistan is part of E9 countries representing more than half of the world population with 70 percent of the illiterate adult population³. Slow progress of the education sector is multi-faceted.

Amongst many challenges, the first major problem that the education sector is facing is the low enrolment rate. There are economic and gender disparities in enrolment across the country with the highest proportion of out of school children in Baluchistan. Most of the out of school children are residing in rural areas (Saeed & Aslam., 2020). This gap widens and the figures are becoming alarmingly high in the middle and high school level⁴. Another challenge is providing uniform and quality education across all the regions. Extensive literature available is available which is evident that quality of education is affected by multiple factors, including

³ National Education Policy Framework (2018)

⁴ Economic Survey of Pakistan (2017-18)

textbooks, curriculum, infrastructure, human and financial resources (Adkins & Moomaw, 1998; Education, 2011; Efficiency & Systems, 1986; Ewell & Ewell, 2010; Hanushek, 2005; Hanushek & Rivkin, 2007; Harvey & Williams, 2010; Jackson, 2009; Jean-Marc, 2014; Singh & Singh, 2010; Young, 2005). Policymakers need to regularly review the learning outcomes and take the necessary steps to improve the efficiency in the educational system because budget allocated to education sector is extremely small.

While we discuss improvement in efficiency in the education sector, we need a systematic approach to measure efficiency. To measure efficiency, we need data on the input and outputs used in the educational process, and it must be compared with the idea or benchmark performance criteria, i.e., production frontier. The main advantage of this technique is that after inefficiency is identified, we can begin to ascertain the root cause and sources of inefficiencies and address it to improve performance. Following are two approaches widely discussed in the literature to measure the production frontier

- Data Envelopment Analysis (DEA)
- Stochastic Frontier Analysis (SFA)

DEA is a non-parametric model which does not require to be functional for the production frontier that is estimated. Besides, there is no statistical issue attached when we are evaluating multiple inputs and output models. However, it does not allow for statistical noise that cannot distinguish between the inefficiencies and the noise. Therefore, it is difficult to estimate reliable efficiency scores. Technical efficiency scores may be more sensitive to the outlier and are upward biased, in case the selected sample is too small.

The alternative approach to estimate the production frontier is the SFA that allows for other sources of inefficiencies in the statistical noise. However, the estimated efficiency score

is sensitive to the choice of the functional form used to predict the production frontier (O'Donnell, 2012). In case of the educational economics, both the DEA and SFA model are applied in many studies to estimate the efficiencies at different levels of educational institutions. (Banker, Rajiv D ; Natranjan, 2008; Chalos, 1997; Davutyany, Demir, & Polat, 2010; Denaux, 2007; Donald, 1999; Fukuyama & Weber, 2002; Heshmati & Kumbhakar, 2007; Houck, Rolle, & He, 2010; Z. Hussain, Mehmood, Siddique, & Afzal, 2015; Johnes, Geraint; johnes, 2009; Primont & Domazlicky, 2006; Ruggiero, 1999, 2007; Sickles, Song, Zelenyuk, Sickles, & Zelenyuk, 2018; Worthington, 2002; Wössmann, 2007).

Other studies approach the Malmquist Index method to measure the Total Factor Productivity (TFP) in the DEA framework, developed by Caves, Christensen, and Diewert, (1982)⁵. Many other researchers to measure the total factor productivity change, technical efficiency change, technological change, scale efficiency change, and pure efficiency change have used precisely this technique. Like Agasisti, Bonomi, and Sibiano, (2014) Agasisti and Dal Bianco, (2009); Bradley, Johnes, and Millington, (2001), Flegg, Allen, Field, and Thurlow, (2004), Johnes, and Ruggiero, (2016), Ouellette and Vierstraete, 2010; Rayeni and Saljooghi, (2010), Worthington, (2002), Hussain et al., (2015). The advantage of the Malmquist Index is that it does not require to assume any functional form for the productivity frontier and assumes that all the decision-making units are efficient. However, it is not multiplicative complete and requires information on the input/output prices, which is difficult, especially in institutional economics, where data availability is an enormous issue. Also, the Malmquist index cannot be represented as the ratio of aggregate input and output index (O'Donnell, 2012) and does not satisfy the property of transitivity; therefore, it can only be used for the comparison of two units at a time. Färe, Grosskopf, Norris, & Zhang, (1994) proposed using the distance function as an

⁵ This approach was based on the early idea of (Malmquist, 1953)

alternative to the Malmquist methodology. Thus, the efficiency measure defined by Farrell (1957) can be measured as the reciprocal of the distance function. The advantage of this measure is that they do not require the data on the input and output prices. O'Donnell (2012) used the distance function approach proposed by Fare-Primont Index to decompose the TFP into technical efficiency change, mix-efficiency change, scale efficiency change, and scale mix-efficiency change⁶. Therefore, this comprehensive decomposition helps us explore the benefits of scale and scope of efficiency change in the production process. Any improvement in the scale and mix-efficiency will increase overall TFP, enhancing social welfare. Thus, this methodology can be used for multilateral and multi-temporal comparisons of different decision-making units (DMUs).

Efficiency in education is essential, given that available resources are scarce, and it gives us the foundation of the economic prosperity of a developing economy. However, there are very few studies available in the area of school efficiency in Pakistan. Few studies evaluated the student and measured school-level performance. A study is available where primary school level efficiency was calculated by Hussain *et al.* (2015) using a Malmquist Index. They used annual data disaggregated into the rural and urban areas of primary schools. Another study by Ahmed (2012) used district-level data for two provinces to estimate efficiency using DEA. However, this study does not use the role of mixed efficiency in explaining TFP. This study uses the district-level data on input and output for Pakistan throughout 2013-167. Due to geographical, cultural, and socio-economic differences, it is more meaningful to analyze the data for each province separately. Each of the provinces is an amalgamation of small and large districts, with some districts performing better than the other. Since the efficiency scores

⁶ Mix-efficiency change and scale mix-efficiency change are not discussed in the Malmquist Index.

⁷ Punjab, Sindh, Khyber Pakhtunkhwa and Baluchistan and this study excludes the districts in Azad Jammu and Kashmir (AJK), Gilgit-Baltistan and Federal Administrated Tribal Area (FATA) due to the unavailability of district-level data on the educational input/output variables

obtained from the first stage ranges from zero to one, they are censored variables and thus an estimation using the ordinary least squares (OLS) will provide biased estimates as suggested by Agasisti (2013). A limited dependent variable model is used to avoid this problem, in this study Tobit model is used to estimate the regression equation (Ramzi et al., 2016; Selim and Bursalıoğlu, 2015).

3.1.1 Objectives of the study

There are multiple objectives that we intend to achieve through this research are

Primary Purpose

- To calculate the efficiency of 113 districts by using a sophisticated econometric technique called Data Envelopment Analysis (DEA).

Secondary Purposes:

- To identify the TFP of underperforming districts
- To calculate the technical, mix and scale efficiencies for each district by decomposing the TFP
- To identify the district/division that is sufficiently efficient
- To investigate the uncontrollable environmental factors⁸ that can explain the differences in the efficiency level

⁸ To measure the district level developmental difference, there are many uncontrollable environmental factors, also called control variables available in the literature. Like competition, number of educational institutions, neighborhood characteristics, location (rural/urban), mortality rate, crime-violence, employment opportunities, poverty rate, population/district size, immigrants and others (Grosskopf & Moutray, 2000; Grosskopf, Hayes, Taylor, & Weber, 2001;Cordero, Santin, & Sicilia, 2013; Crespo-Cebada, Pedraja-Chaparro, & Santin, 2014; Grosskopf, Hayes, & Taylor, 2014; CMG Haelermans, 2012; J. Johnes, 2015; De Witte & López-Torres, 2017). However, the three main dimensions that are considered to measure the development of a country includes, education, health and the living standard, which will be used in this section to measure the differences across the district.

Investigation of the overall TFP and the TFP for the four provinces separately can help policymakers make better policy-related decisions for each province.

3.1.2 Significance of the study

Although the research in educational efficiency is very vast, the policy outcomes that can be extracted from it are limited. We can find consistency in the research findings; however, the schools differ drastically because a single policy cannot be implemented in all the schools. Policymakers are more interested in the factors that explain the difference in the performance due to changes in the expenditure, physical and human resources. Whereas the differences are mainly due to some external factors including the geographical difference, living standard, and health conditions. Most of the research in education is empirical; therefore, it is crucial to understand the conceptual model. Production theory has been widely discussed in textbooks; however, its implication in educational production is limited. Thus, it is imperative to discuss the concept of efficiency in the area of education, which has not been extensively discussed.

3.1.3 Contribution of the study

This paper contributes to the literature by using the Fare-Primont index to calculate TFP and its components to analyze the district-level data of educational input and outputs. Further, in the area of education, only a few research papers have followed the idea of non-parametric modeling to estimate the scale and mix-efficiency using the technique developed by O'Donnell (2010). This study additionally extended the methodology by analyzing the effect of environmental factors in explaining the difference in the efficiency level of each district in each province of Pakistan.

3.1.4 Structure of the Paper

Section1: provides a brief introduction of the search topic along with the research objects, significance, and contribution of the study.

Section 2: Literature review discussed the students that performed district-level analysis. Further, this section also analyses the input and output variables that are used in the literature. Different performance indicators and variables that are used in the literature, with their significance is discussed.

Section 3: Discusses in detail the methodology that is used in the study (O'Donnell, 2008) proposed to use the data envelopment analysis, linear programming model to calculate the total factor productivity and the components of efficiency.

Section 4: Data and results are presented in this section. Descriptive analysis is discussed along with the brief demography of the region-wise divisions of the districts. TPF and efficiency components are discussed at level, and indexes are also discussed. The aggregated data are represented at the division level so that performance can be evaluated more accurately. In the second step, Tobit model is used to investigate the determents that can explain the difference in the efficiencies calculated in the first step.

Section 5: Conclusion is reported in this section, along with the policy implications and recommendations.

3.2 Literature Review

3.2.1 Defining Efficiency in Education

The idea about the educational efficiency is not new and was first discussed in the early '50s, however, formally discussed in the Coleman-report (Coleman et al., 1966). Though the idea of efficiency seems quite simple, it is complicated in the educational sector. Fried, Lovell, and Schmidt (1993) define educational efficiency by comparing the optimal level of inputs to the observed input levels used in the school's productivity. The comparison can be in terms of the ratio between the observed and the maximum potential value produced with the given inputs. On the other hand, the ratio could also be between observed values for the minimum input

required to produce the given level of output. Another study discusses the input-output ratio as technical efficiency only if we can increase the output by decreasing the output of other production processes (Koopmans, 1951). However, the definition of technical efficiency by Koopman (1951) was revisited and was defined in relative notations by Farrell (1957) and Charnes & Cooper (1984). Thus, comparing the observed technical efficiency with the best-practiced reference group helped to distinguish between efficient and inefficient production units. However, this definition ignored the discussion on how efficient production can be identified. Moreover, on how the degree of inefficiency compared to the efficient unit can be determined.

Debreu (1951) discusses productive efficiency by introducing the concept of the utilization of resources. Debreu's measurement of efficiency is based on technical efficiency (Koopmans, 1951). He stated about the feasibility and equi-proportionate minimum inputs used to produce the given output maximum feasible and equi-proportionate output that can be produced with the given input levels. Extending the work of Debreu and Koopmans, Farrell (1957) believes there is a second component in the productive efficiency and the technically efficient input-output vector, i.e., the prices of inputs and outputs. Therefore, referring to the fact that production efficiency is the combination of both allocative and technical efficiency. The majority of the economist's focus is on the market, and thus prices work as an invisible hand in the allocation of resources. Although most economists are more concerned about allocative efficiency, but it is difficult to accurately measure the price that can result in a fair distribution of resources. According to Hoxby (1996), allocative efficiency in education refers to the quality, type, and amount of schooling provided (optimal number), whereas the technical efficiency refers to the objective of cost minimization through the given set of goals. Adnett and Davies (2002) defined school efficiency as the maximization of outputs based on the given level of resources. Another study defines scholarly output as allocative efficiency based on

revenue maximization, given that the schools are technically efficient (Kirjavainen, 2009). However, this definition seems narrow as a set of inputs used in calculating efficiency is limited and ignores many dimensions that need to be considered: family background, social infrastructure, students' behavior, and other aspects (Johnes *et al.*, 2017; Hoxby, 1996).

Efficiency in education depends on multiple inputs and results in multiple outputs, whereas the single output is produced in other production processes. These unobserved dimensions (factors) correlate with educational performance and affect the efficiency of the school. Thus, provide biased results at the time of comparison of educational systems and raises serious concerns.

Many studies in the educational literature discussed the issue of efficiency; however, in this study, we focus on district-level analysis. Heshmati & Kumbhakar (1997) is one of the earliest contributors in the efficiency literature. This study uses the Stochastic Frontier Analysis for the measurement of productivity and cost function. Maximum likelihood estimation was used for parameters, based on which the efficiency score was predicted. Data from 286 municipalities were collected for primary and secondary schools for the year 1993-94. The analysis concludes that most of the schools in the sample operate in the efficiency level from 85 percent to 100 percent. The average efficiency is found to be in the interval 90-92 percent, which indicates that Swedish Municipal school can improve the production capacity by 8 to 10 percent through the policy change.

Another group of researchers discussed the efficiency in student achievement and its tradeoff with equality. Some also considered the budget constraint in the estimation process (Anderson & Silver, 1984; Grosskopf, Hayes, Taylor, & Weber, 1997; Thomas, Wang, & Xibo, 2002; Domović & Godler, 2005; Benito, Alegre, & González-Balletbò, 2014). These researchers are of the view that efficiency and equality are keys to educational policies. In an

analysis by Grosskopf et al., (1997), they view that even in the inefficient district school, financial reforms can play an important role and can guarantee gains in the student's efficiency. Versteegen (1994) investigated the same issue in American schooling and concluded that irrespective of the outliers, not all state schools show the same increase in efficiency after the financial reforms. Moreover, it can be seen that richer states have more influence on the decision-making and have more revenues that are eventually increasing the gap between equality and efficiency for the rich and poor states.

3.2.2 Empirical Review of Methodologies Used To Measure Efficiency

There are four primary methods used in the literature to measure efficiency. The first one is the least square econometric production models, and the second method is through total factor productivity indices, the third one is the data envelopment analysis, and the last one is the stochastic frontier method. The first and the second methods are more commonly applied to the time series data to measure the productivity change over time; however, they can also be used to measure the relative productivity of cross-sectional data at one point in time. Hence, the productivity measure does not assume that the DMU is technically efficient. The DEA and SFA are more commonly used for cross-sectional analysis; however, they can also be used to measure the efficiency changes over time if the cross-sectional data are available. In this study, we use the decomposition of total factor productivity to measure different components of the school's efficiency.

Traditional educational inputs and outputs have an impact on the efficiency level in the field of education, which has been explained by (De Witte & López-Torres, 2017), in their study. They held a view that the impact of standard inputs, outputs, and variables in the educational field are because of teachers and the learning environment, which in turn affect the entire efficiency level. Hence, it is crucial to accurately figure out the outcomes of environmental variables on student learning and to present a basic structure which sources the

efficiency level and make efficiency processes more effective and accurate. Nonparametric (DEA, FDH, order-m frontiers) and parameters (SFA) frontier methods have been used to analyze the education efficiency at district-level schools. To establish a systematic link between institutional economics and educational efficiency, they both used recent models such as the conditional efficiency and meta-frontiers, quantile regressions, and partial frontier's method. Investigations exhibited that the research on school effectiveness demands to consider all variables which affect educational institutions and student learning outcomes for academic and social development in particular, and the entire educational system, in general. Here, both scholars have elaborated that what we could learn from institutional economics and educational efficiency and how we can compare certainly, those methodological techniques used by the other scholars of educational efficiency (De Witte & López-Torres, 2017). They both also analyzed the resemblances between matching and conditional efficiency, at different levels, including the district-level analysis along with the determinants of education, which affect the efficiency level. It has been observed that insights into the resemblances can aid in developing further research on educational efficiency.

The level of efficiency measure defined by Koopmans (1951) is very much similar to what is estimated using the Farrell index. The main idea is that the production possibilities cannot be increased without increasing the inputs. The DEA approach is based on the Farrell Index, in which a reduction in observed input is necessary for the given level of output. Although the efficiency is achieved, some slack may exist due to the implicit restrictions on the model assumption, i.e., restrictions on the weights of the input and output variables. Slack model is applied in many different fields to measure the efficiency of the decision-making unit (Agha, Kuhail, Abdelnabi, Salem, & Ghanim, 2011; Ahec Sonje, Deskar-Skrbic, & Sonje, 2018; Koltai & Uzonyi-Kecskés, 2017; Morita, Hirokawa, & Zhu, 2005; Soteriou, Karahanna, Papanastasiou, & Diakourakis, 1998; Sueyoshi, Ohnishi, & Kinase, 1999; Tali, Padi, & Dar,

2016)). However, in the case of school efficiency, few studies could be found, e.g. (Agha et al., 2011; Ahec Sonje et al., 2018; Soteriou et al., 1998).

A comparison of public and private school achievement is performed by McEwan and Carnoy (2000) for Chili. This study initially used a complete set of student achievement and background data than other studies. Second, it divides voucher schools into three categories—Catholic, Protestant, and non-religious—instead of lumping them together (as it turns out, their effectiveness and costs are quite different). Third, it is the only comprehensive analysis of costs and efficiency. A comparison of public and private schools is made using the multi-product cost function, and the Cobb Douglas production function was used for the analysis. The study concluded that a privately run school is slightly less effective than public schools. Non-religious private voucher schools, when they are located outside of the capital, are even less effective than public schools. Performance differences can be explained by the higher fraction of teachers who have short-term contracts.

Additionally, Catholic schools are observed to be more effective than public schools, as similar students achieve a higher rate of productivity. However, there is a possibility that selection bias could have contaminated the selection of private school effects. Eventually, if the peer affects the student performance, then sorting such an outcome effect could not be measured.

Another study by Primont and Domazlicky (2006) measured the effect of supplemental tutoring and school transfer under no child left behind policy. School efficiency was calculated by using the two-step Data Envelopment Analysis. During the first stage, regression analysis was performed using the seemingly unrelated model (SUR) model on 355 schools out of 522 at the district level. In the 2nd stage, DEA analysis was conducted in 309 districts out of 355 school districts selected at stage 1. The targeted output at stage 1 was test scores of arts, science,

and reading. The input used the test scores for year 1998 of all these subjects to control the student's ability, socio-economic background of a family (students receiving free lunch, occupation). Student demographics (minority, non-white, population per square mile, the population in 2000 and 1995) and Incident rate involving student suspensions were also considered for the analysis. In the 2nd stage, Quasi fixed inputs used are the characteristics of the teacher (master's degree) and admin (average years of experience), Facilities (number of computers), capital expenditure per student, transportation services, purchased services, and other expenditure. Variable inputs are admin staff per student, no. of teachers per student.

Further, for the estimation of allocative efficiency, input prices, i.e., admin salary, average annual teacher salary, amount of spending on teachers, and administrators per student, are considered. The study concludes that technical inefficiency is significantly higher for failing schools than the passing schools, while there was no significant difference in allocative inefficiency in the two groups of schools. The transfer of a student's sanction is more likely to improve managerial efficiency than the tutoring services sanction. However, the question arises that why any federal government is willing to invest in schools that are already failing. Oliveira et al., (2006) investigated the efficiency of Secondary Education in Portugal and used FDH with Bootstrapping to measure efficiency score and slacks, by relaxing the assumption of convexity. Student's data from 42 public schools for the year 1999-2000 was considered for the analysis. Student performance for 1st, 2nd, and 3rd year was used as the dependent variable, and explanatory inputs considered are from the domains like educational environment, 26 items; education, teaching, and learning, 26 items; organization, and management, 97 items. The study concludes that at the district level analysis, living infrastructures, adult education, access to health, and the unemployment rate are significant determinants of school efficiency. Hence, the schools in major coastal metropolitan areas are more efficient than others.

Some researchers, including Grosskopf & Moutray, (2001) Smith and Street, (2006) also used the DEA to decompose changes of efficiency over time into technological progress and efficiency gains, using a Malmquist index approach. The analysis mainly focused on calculating the Technical and allocative inefficiency in the education sector (Essid, Ouellette, & Vigeant, 2014; Aparicio, Crespo-Cebada, Pedraja-Chaparro, & Santín, 2017). Cross-sectional data of 2928 schools for the year 2003-04 was considered. The value-added attainment of pupils of grade fourth compared to grade third is considered as the performance measure (Smith & Street, 2006). Several teachers, the number of learning support staff, admin and clerical staff, expenditure of learning resources are the explanatory variables used. Also, the set of control variables used are pupils with no free lunch, special needs, and English as an additional language. The findings of the study suggest that neither the fact that the magnitude of allocative efficiency is not doughy relatively high, but the technical inefficiency is a more critical factor that needs to be tackled (Smith & Street, 2006).

Consequently, if the study could use the DEA estimates for inter-school benchmarking, then in doing so, the limitations of data and modeling assumptions need to be explained very carefully. If additional years' data become available, the DEA could also serve as a basis for examining productivity gains using the Malmquist index approach. Hussain, Mehmood, Siddique, and Afzal, (2015) also used a similar technique to decompose the productivity into the technical scale and total factor productivity change, to analyze if the educational resources are being properly utilized or not. The analysis was disaggregated for the urban and rural areas. The results conclude that under a constant return to scale (CRS) and variable return (VRS) to scale public schools were observed to be technically inefficient. However, the performance is satisfactory overtime when the scale, pure efficiency, and the technical efficiency change was measured.

Houcky, Rolle, & He, (2018) examined the productive efficiency of school districts by using a modified quadratic form method, where both the graphical and quantitative differences are considered while making analysis. The fundamental question they tried to answer was Why one school or district produces more than another, and what a hypothetical "most efficient" school or school system would look. This study revealed persistently efficient and effective districts; there were no persistently ineffective or inefficient districts overall five outcome measures (Houck et al., 2010). Spending on instructions has a positive effect on efficiency and effectiveness. Like the other states who applied the same methodology, efficiency is affected by the demographics, local wealth, and school district performance. However, a panel data analysis could provide a clearer picture of overtime changes.

Student performance is the outcome of an individual's effort, family characteristics, and school-level resources. Raposo, Isabel; Menezes, (2011) view that efficiency can only be explained, if the explanatory variables can be separated from the school resources and practices followed in schools. The DEA two-stage model is used to estimate the efficiency of 4th-grade students on the math test. Exogenous inputs include student enrollment, school physical resources, the faculty member's characteristics, and grade progression. The results suggest that in a 2 stage DEA model, the ranks for estimating efficiency scores are much more homogenous than the one-stage model. However, the literature showed mixed results to support this finding as operating conditions and practices need to be considered while making performance comparisons (Johnson & Kuosmanen, 2012).

3.2.2 Studies from Pakistan

Unlike the above-mentioned literature, in Pakistan, yet no direct studies have been conducted on TFP while taking into account the performance of schools at district level analysis. A voluminous literature could be found to analyze the performance and quality of district-level schools in Pakistan; however, researchers have conducted most studies on specific

districts, e.g., Case study of a province or a district rather than the entire Pakistan district-level school's analysis.

To assess the school performance and to understand which schools are doing better H. Khan, (2003), analyses the quality of education and school performance at the district level. This study's critical attention was to evaluate the learning outcomes of students of both public and private schools in Pakistan through grade five student's achievements. For this purpose, he randomly selected 12 districts from all over the country from each district (12 primary schools, 8 governments, and four private schools were sampled), and from each school, (20 students of 5th class were sampled) for the assessment process. The overall sample consisted of 3442 (boys 1943 and girls 1499 students). For more effective assessment, he also concerned the rural and urban ratio in which (1724 urban students and 1718 rural students) were involved. Thus, to gauge the opinion of teachers about the quality of education was also involved in the assessment process. This research mainly tried to evaluate the learning achievement and outcomes of grade-5 students of both public and private schools in Mathematics, Science, and Language (Urdu).

H. Khan, (2003), tried to identify crucial aspects that affect the quality of education and performance of a school, e.g., teachers' characteristics, the availability of physical facilities in the school, and other socio-economic factors. Along with the quest to find the rapport between scores and the independent variables, the study correlated not only teachers' characteristics, but also the parental characteristics, and school attributes. In comparison, he also included teachers' qualifications, socio-economic status of the students, and the accessibility of infrastructure in the schools. He projected a detailed outline of those aspects that stimulus student performance and suggested that the availability of improved and modern facilities and infrastructure could

enhance the internal efficiency of the education system as these elements have had a direct link with the performance of the students.

Another district-level case study designed by Salfi & Saeed, (2007) elaborated that school culture has a linkage with students' achievement and performance. To study this linkage, they divided the districts into four cultural areas and sampled 2,924 government high schools (from 36 districts) of the Punjab province (besides with a sample of 90 head teachers and 540 teachers). In addition, to study the variable cultural effects on students' performance, they employed a stratified and simple random sampling technique and divided the more than a half sample into rural and less than half into urban areas. The outcome of this assessment proves that cultural variables impose an immense impact not only on the efficiency and on the performance of students and schools, but on the teacher's performance, also which then affects the entire efficiency level of a school.

To study the effect of the teacher's performance Amin, Ullah Shah, Ayaz, & Atta, (2013), exhibited another district-level case study to explore the performance of teachers at secondary school level in the Khyber Pakhtunkhwa district. They involved a random selection of the inhabitants from four districts (i.e., Kohat, Karak, Bannu, and Lakki Marwat). The analysis of the collected data accomplished through mean and standard deviation methods to serve the research questions while keeping the teacher's performance as a variable. For evaluation of the teacher's performance, a self-rating questionnaire (TJPSQ) was established. The researchers evaluate the teacher's performance to monitor and gauge quality, efficiency, and school performance, and through this, they provide an extensive data analysis of the teacher's job performance.

It is obvious that there are several factors which hinder the performance of schools and for this purpose Nadeem et al., (2011) made a detailed descriptive examination for the

identification of all those factors which influence the performance of teachers (specifically for female teachers) in rural and urban areas of Bahawalpur. They adopted the survey method for data collection and for the identification and analysis of those factors. They concerned the sample of 1020 students and 204 teachers of higher secondary schools to generate the results, and thus they found that most factors and the performance of teachers have had an association between them. They viewed that teacher performance acts as a catalyst in the field of education, and they recognize some factors that influence teacher performance, e.g., External and internal factors, and studied that internal factors and many external factors can affect the teacher's success. It is evident that the availability of resources plays a decisive role in increasing or decrease school performance. Thus, their analysis concluded that adequate pre-and in-service teacher training courses should be employed in the education sector, which will source the effectiveness, creativity, and improvement in the field of pedagogy. And the closest attention should be paid to the utilization of the latest, relevant techniques and technologies in teacher education to enhance the school performance.

For the evaluation of school performance of District Sukkur S. Hussain, (2018), calculated the student's performance in mathematics and science subjects. Through standardized achievement tests, the researcher tried to discover the attributes of government primary schools and make an evaluation of class IV student's performance in Mathematics and Science subjects. He conducted these tests in 55 public primary schools of Sukkur. The researcher examined the testes (in girls' schools, boys, schools, and mixed-gender schools), and after analyzing the obtained results, he suggested that all physical and infrastructural resources should be provided at primary levels for the expansion of school performance. Although, there are still many other variables and factors which hinder the efficiency, quality, and specific performance level.

Students learning achievement are considered as one of the indicators to measure school characteristics, although the evaluation process possesses many gaps. However, to reduce the gaps in the evaluation of academic performance in Pakistan government schools Hayat, Nisar, Sajjad, Abbas, & Raza, (2018), analyzed the students' academic performance concerning social media usage, physical activity, and motivation. A sample of 204 students was selected who were studying in different government schools in district Lahore. Both stratified random sampling and simple random sampling techniques are adopted to draw the sample. To analyze the performance of ninth and tenth grade students both correlation and regression analysis were used to analyze the data. All the predicted variables were measured in quantitative terms and evaluated with statistical techniques. This study just focused on a few factors to determine the students' academic performance and not include other factors like demographic factors. They concluded that, generally, different factors could influence the performance, such as the attitude of students, the teacher's attitude, family background, school environment, and school location.

The other factors and variables which affect the school outcomes are explained by Asim & Dee, (2016), who provided evidence that how the critical school outcomes influence the entire curriculum period (e.g., Average enrolment of a student, functioning of school facilities, and teacher attendance). They primarily collected data from the publicly available school-level administration and regularly collected by the Program Monitoring and Implementation Unit (PMIU) of the Punjab School Education Department. They calculated the data from 26 (primary and middle schools) out of the 36 districts of the Punjab. To measure critical school outcomes and to estimate the effects of factors, "intent to treat" (ITT) method employed on a "difference in differences" specification. The comparative data collected for the untreated 21 districts provided information on the existing and the potential direction of biases in DD inferences. On the contrary, data collected from the 26 districts facilitate a "triple difference" (DDD) approach that isolates the impact of interest while considering the SCMP participation

as a dependent variable. This unique calculation also examines the SCMP's effects on student and teacher attendance, school enrolment, and school facilities by using an SCMP based "difference in difference in differences" (DDD) design. Furthermore, this concise study discusses and evaluates a scalable, low-cost program that was designed to improve the administration and performance of primary and middle schools in Punjab.

Similarly, another paper presented by Mujahid & Noman, (2015) analyzed the efficiency of 48,865 Government schools. They both investigated that a disciplined and efficient allocation and resource utilization can boost up a specific efficiency level. The exclusiveness of this research work is that it assimilates a wide range of microdata variables for the year 2011-12. Both scholars explored that increased Total factor Productivity (TFP) depends upon the skilled human resources and high literacy rates and, also expands the economic growth of the country.

To recognize the authentic performance and condition of primary schools (Laghari, Abro, & Jamali, (2013), contributed through a stratified random sampling technique and selected (500 students, 200 teachers, 200 parents, and 80 officers), from the public primary schools of Sindh. The researchers discuss the contributions of students, teachers, parents, and officers towards the promotion of a school's performance. They pointed out that the infrastructure of the school and physical facilities, medium of instruction, drop out of students, curriculum introduction and implementation, teacher's attributes, the system of examination, the performance of students are some significant variations. All these have a progressive impact on school performance; thus, schools should be equipped with proper infrastructure along with other resource availability.

Researches have articulated that some micro and macro variables contribute towards the education system performance. Kiani, (2013) aimed to explore the macroeconomic

variables and examined the significance of some key macroeconomic variables on Pakistan's economic growth during 1980-2009. researcher evaluated the variables at four different education levels (i.e., Primary, Middle, and High school) and identified some other variables, including import and export, and Basic health unit (BHUs) as main macroeconomic variables. In the output evaluation process, a simple growth model is used to equate the macroeconomic variables. This study also led a factual inquiry of the factors that have an immense effect on economic growth in Pakistan from 1980 through 2010. Eventually, she generated the consequences through the linear regression model and provided a strong impact of these variables on school performance.

For the quest, to provide and assess the learning outcomes of children aged between 5-16 and the reflection of educational outcomes among urban and rural areas, ASER Pakistan prepared Annual Education Report in 2019 (across 155 rural and 20 urban districts). Saeed & Aslam, (2020), also worked to gather primary data to evaluate key education outcomes since 2010 from across Pakistan which is the largest citizen-based survey,. This survey articulates a concise outline of the learning competencies of out of school and in-school Pakistani children. The research team of ASER has spent over 15 years examining ways to improve learning outcomes in Pakistan, and for this purpose, they initiated a Learning and Achievement in Pakistan Schools (LEAPS) program. Through, LEAPS program, they investigated and presented some findings on how learning outcomes for children in contemporary education can be enhanced.

As it is evident from the above-mentioned gray literature, we could not find enough studies to measure the performance of schools using total factor productivity or efficiency. Thus, this research is a contribution to develop a study to analyze the performance of schools in Pakistan at the district level through total factor productivity measures.

3.3. Methodology

3.3.1 Total Factor Productivity and Fare Primont Index

Increasing the efficiency in educational production by using the same amount of resources to produce a higher level of output is critically essential for improving social welfare. TFP is used to measure the efficiency of the educational system at the district level. The productivity of a firm with 1 input and 1 output is defined as the ratio of output to input. However, with multiple inputs and multiple outputs, the concept of total factor productivity is defined as the ratio of aggregate output to aggregate input. Following O'Donnell (2010), we can define Fare-Primont TFP index using the set of $i= 1 \dots Ni$ decision-making units (DMUs) over the period $t = 1 \dots T$. Each DMUs is using $x_t \in \mathfrak{R}_+^X$ inputs to produce $q_t \in \mathfrak{R}_+^Q$ level of output. The benchmark technology set for a period can be defined as follows

$$\Psi^t = \{(x_t, q_t): x_t \in \mathfrak{R}_+^X, q_t \in \mathfrak{R}_+^Q, x_t \text{ can produce } q_t\} \quad (3.1)$$

Where $x_t \in \mathfrak{R}_+^X$ is the vector of inputs quantities and $q_t \in \mathfrak{R}_+^Q$. Thus, the TFP for the i^{th} DMU at period t is as below

$$TFP_{it} = Q_{it}/X_{it} \quad (3.2)$$

Where $Q_{it} = Q(q_{it})$ represents the aggregate output and $X_{it} = X(x_{it})$ represents the aggregate input of the i^{th} DMU at period t . Further, the aggregating functions $Q(\cdot)$ and $X(\cdot)$ are non-decreasing, non-negative, and homogeneous of degree 1. O'Donnell (2012) is of the view that different types of aggregate functions result in different types of index numbers. The TFP index for the i^{th} DMU in period t and h^{th} DMU in period s can be defined as the

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it}/X_{it}}{Q_{hs}/X_{hs}} = \frac{Q_{it}/Q_{hs}}{X_{it}/X_{hs}} = \frac{Q_{hs,it}}{X_{hs,it}} \quad (3.3)$$

Where $Q_{hs,it}$ is the index of output quantity, which is the ratio of aggregate output of the i th DMU in period t and h th DMU in time s . Similarly, $X_{hs,it}$ is the index of input quantity, which is the ratio of aggregate input of the i th DMU at time t and h th DMU at time s . It can be seen that if the index of input quantity is fixed, then the TFP index depends on the index of output quantity; if the DMU is fully efficient, then it is referred to as the output-based productivity index. Similarly, if the output quantity index is fixed, then the change in the TFP index depends on the index of input quantity. If the DMU is fully efficient, then it is referred to as the input-based productivity index (Caves et al., 1982). The aggregation function used the distance function following Shephard (1970) and defined the output (D_O^t) and input (D_I^t) distance function as follows

$$D_I^t(x_t, q_t) = \max_{\rho} \{\rho > 0: (x_t/\rho, q_t) \in \Psi^t\} \quad (\text{Input oriented distance function})$$

$$D_O^t(x_t, q_t) = \min_{\delta} \{\delta > 0: (x_t, q_t/\delta) \in \Psi^t\} \quad (\text{Output oriented distance function})$$

The input distance function refers to the minimum level of input that can be used to produce the same level of output. In other words, the most significant factor by which the DMU can reduce its input vector to produce the fixed level of the output vector. Similarly, output distance function refers to the maximum level of output that can be produced with the given level of inputs. Alternatively, it can be defined as the maximum factor by which DMU can scale up its output vector with the fixed level of the input vector. For a fully efficient and technically feasible DMU the combination output (D_O^t) and input (D_I^t) distance function should be equal

to unity. As discussed, earlier TFP index (TFPI) is the ratio of the aggregate output quantity index and the aggregate input quantity index, thus it can be defined in terms of the distance function as

$$Q_{hs,it} = \frac{D_O(x_0, q_{it}, t_0)}{D_O(x_0, q_{hs}, t_0)} \quad (3.4)$$

$$X_{hs,it} = \frac{D_I(x_{hs}, q_0, t_0)}{D_I(x_{it}, q_0, t_0)} \quad (3.5)$$

Fare- Primont productivity index based on the distance function can be defined as

$$TFPI_{hs,it} = \frac{D_O(x_0, q_{it}, t_0) D_I(x_{hs}, q_0, t_0)}{D_O(x_0, q_{hs}, t_0) D_I(x_{it}, q_0, t_0)} \quad (3.6)$$

where, $x_0 \in \mathfrak{R}_+^X$ and $q_0 \in \mathfrak{R}_+^Q$ represents the fixed weights for the input x and q , which is the sample mean and $t_0 \in \mathfrak{R}_+$ is the fixed period for the sample under analysis. The $TFPI_{hs,it}$ thus defined satisfied the set of axioms, including weak monotonicity, homogeneity, identity, proportionality, time-space reversal, transitivity, and circularity (O'Donnell, 2013, 2017).

3.3.2 Decomposing Total Factor Productivity and Measuring Efficiency

Many different approaches, discuss the decomposition of TFP index. However, two main approaches got prominent (Balk & Zofio, 2018; Caves et al., 1982; Diewert & Fox, 2014; Grifell-Tatjé & Lovell, 1995; Nemoto & Goto, 2005; Peyrache, 2014). The first approach combines the efficiency and technical change to form the TFP index (e.g., Balk & Zofio, 2018). This approach is also referred to as the bottom-up approach. The second approach discusses the decomposition of a recognizable TFP index into technical and efficiency change components. (e.g., Grosskopf & Moutray, 2000). However, the methodology developed by

O'Donnell, (2008) uses the main features of both approaches by first using the input and output aggregation functions to define the measures of efficiency and technical change and defined the TFP index. Further, the multiplicatively complete TFP index thus obtained is decomposed into different components of technological, technical, scale and scope efficiency change. In this study, we are using the output-oriented decomposition of the TFP under the variable return to scale (VRS) in the education sector as the government wants to maximize the output level with the given input level of human and physical capital inputs.

The idea about the educational efficiency is not new and was first discussed in early 50's however, formally discussed in the Coleman-report (Coleman et al., 1966). Though the idea of efficiency seems quite simple, but it is complicated in the case of the educational sector. Fried, Lovell, and Schmidt (1993) defines educational efficiency by comparing the optimal level of inputs to the observed input levels used in the school's productivity. The comparison can be in terms of the ratio between the observed and the maximum potential value that can be produced with the given inputs. On the other hand, the ratio could also be between observed values from the minimum input required to produce the given level of output. Another study discusses the input-output ratio as technical efficiency only if we can increase the output by decreasing the output of other production process (Koopmans, 1951). However, the definition of technical efficiency by Koopman (1951) was revisited and was defined in relative notations by Farrell (1957) and Charnes & Cooper (1984). Thus, comparing the observed technical efficiency with the best practiced reference group, that helped in distinguishing between the efficient and inefficient production units. However, this definition ignored the discussion on how efficient production can be identified? and the degree of inefficiency compared to the efficient unit.

Consider the DMU at point A with that it produces an aggregate output of Q_{it} with the aggregate input of X_{it} (Figure 1). The point A is clearly an inefficient point to operate as it is below the maximum possible production possibility frontier. O'Donnell, (2008) defines the TFP at point A as the slope of OA (Q_{it}/X_{it}) and the TFP at point C as the slope of OC (\bar{Q}_{it}/X_{it}) (Figure 1) i.e., the point on the efficient frontier. Thus, the output oriented technical efficiency (OTE_{it}) can be defined as

$$OTE_{it} = \frac{Q_{it}/X_{it}}{\bar{Q}_{it}/X_{it}} = \frac{Q_{it}}{\bar{Q}_{it}} \leq 1 \quad (3.7)$$

Where, \bar{Q}_{it} is the maximum level of aggregate output possible using the x_{it} level input to produce scalar multiplier of q_{it} . The range of efficiency components lie between 0 and 1 i.e., 0 is the lower limit representing the inefficient unit and 1 represents the fully efficiency DMUs that lie on the production possibility frontier.

O'Donnell, (2008) associated the TFP with economies of scale and scope and defined the Output-oriented Scale Mix Efficiency as ($OSME_{it}$) as the product of Output-oriented Mix Efficiency (OME_{it}) and Residual Output-oriented Scale Efficiency ($ROSE_{it}$). The maximum TFP_{it} output mix that can be achieved by given level on input X_{it} is represented by the slope of OV (\hat{Q}_{it}/X_{it}). Thus, the distance between the TFP at point C and the TFP at point V represents the mix inefficiency. OME_{it} can thus be represented as ratio between slope of OC (\bar{Q}_{it}/X_{it}) and the slope of OV (\hat{Q}_{it}/X_{it}) as follows

$$OME_{it} = \frac{\bar{Q}_{it}/X_{it}}{\hat{Q}_{it}/X_{it}} = \frac{\bar{Q}_{it}}{\hat{Q}_{it}} \leq 1 \quad (3.8)$$

Where, \hat{Q}_{it} is the maximum level of aggregate output that is produced using technically feasible x_{it} and achieved output vector. It can be seen from figure 1 that an inefficient firm

starting from point A can move improve its TFP by moving to a technically efficient point C and even a higher point V through mix efficiency but both these points do not represent the maximized TFP. Rather, TFP is maximized where the ray through the origin is tangent to the production possibility frontier (in our case PPF₂). Thus, a movement from mixed efficient point V to a maximized TFP* is represented by point E, also referred to as the $ROSE_{it}$. The mathematical representation is as below

$$ROSE_{it} = \frac{\hat{Q}_{it}/X_{it}}{TFP_{it}^*} \leq 1 \quad (3.9)$$

where, $TFP_{it}^* = Q(q_{it}^*)/X(x_{it}^*)$ and $ROSE_{it}$ is the component remaining after accounting for the technical and the mix efficiency.

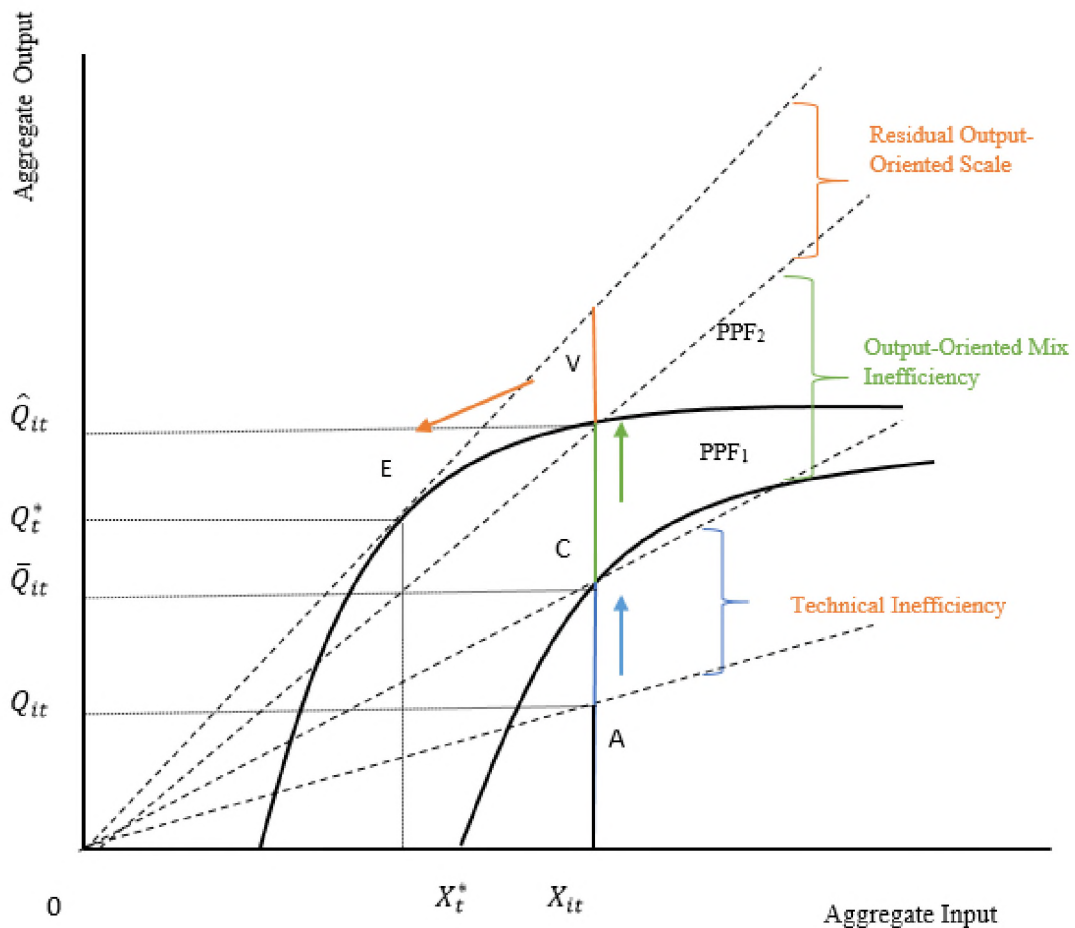
With the help of efficiency measure defined about we can now measure the Total Factor Productivity Efficiency ($TFPE_{it}$) as

$$TFPE_{it} = OTE_{it} \times OME_{it} \times ROSE_{it} \quad (3.10)$$

$$TFPI_{hs,it} = \left(\frac{TFP_{it}^*}{TFP_{hs}^*} \right) \times \left(\frac{OTE_{it}}{OTE_{hs}} \right) \times \left(\frac{OME_{it}}{OME_{hs}} \right) \times \left(\frac{ROSE_{it}}{ROSE_{hs}} \right) \quad (3.11)$$

Equation (3.10) shows the efficiency measures of i^{th} DMU in time t . Whereas the equation (3.11) shows the technological change, technical change, mix efficiency change and residual scale efficiency change of i^{th} DMU in time t and the s^{th} DMU in time h . The decomposition of the TFPI is said to be complete in a sense that there is not there is no unexplained component left.

Figure 3.1: Output Oriented Decomposition of Total Factor Productivity



3.3.3 Tobit Model

There are many methods discussed in the literature regarding the inclusion of environmental variables. However, the researchers do not agree to one method which is preferred to an alternate methodology that is available. However, the two-step DEA model has been employed widely in the literature. This approach used the efficiencies calculated in the first step, and the non-discretionary variables are then regressed on the efficiency score. Simar and Wilson (2007) suggested to use the truncated model based on the drawback that Tobit model does not necessarily include/identify the important variables that are used in the model. In another study by Simar and Wilson (2019) they suggested to use the two-stage estimator based on bootstrapping. Daraio and Simar (2005) in another study used the robust conditional estimators

like alpha-quantile and order-m frontier approaches to analyze the effect of environmental variables. Similar approaches were also used by Kounetas et al (2011), Wolszczak-Derlacz and Parteka (2011), Lee (2011), Mancebón et al (2012), Johnes et al (2012), Burney et al (2013), Duh et al (2014) and others. The robust approach of conditional estimators is also used for the non-parametric models (De Witte and Kortelainen, 2017).

Since the efficiency scores obtained from the first stage ranges from zero to one, they are censored variables and thus an estimation using the ordinary least squares (OLS) will provide biased estimates as suggested by Agasisti (2013). A limited dependent variable model is used to avoid this problem in this case the Tobit model is used to estimate the regression equation. Tobit Model is a discrete model where some of the observations are missing out of a certain range of variables in the regression model, so the unavailability of observations limits the range of variations in the dependent observed variable. The censored model is available when at least the independent variables are observable and available (Üçdoğruk, Fahamet, & Hamdi, 2001). Therefore, Tobit model is used in the study, which is as follows:

$$y_i^* = x_i^T \beta + u_i \quad (3.12)$$

Where y_i^* is the dependent variable, and x represents the vector of dependent variables, β is the vector of unknown parameters. The range of y_i^* is defined as follows:

$$y_i^* = \begin{cases} x_i^T \beta + u_i, & y_i^* > 0 \\ 0, & y_i^* < 0 \end{cases} \quad (3.13)$$

The Maximum Likelihood estimation is used to obtain the estimated parameter values, and the error term is assumed to be normally distributed, further is consistent and asymptotically normally distributed (Üçdoğruk et al., 2001)

3.4 Data and Results

All the districts in Pakistan are considered as the targeted population to measure efficiency. This study excludes the districts in Azad Jammu and Kashmir (AJK), Gilgit-Baltistan and Federal Administrated Tribal Area (FATA) ⁹ due to the unavailability of district-level data on the educational input/output variables. There are 156 districts across all regions/territories of Pakistan. However, for this study only 112 districts are selected as a sample.

Distribution of districts across all the regions and territories in Pakistan is presented in Table 3.1. Further, the table shows the total schools based on the population and the area of the region.

Table 3. 1: Overview at All the Regions and Territories in Pakistan

This table shows the geographical distribution of regions and territories in Pakistan. Further, population density and total number of schools in provinces are mentioned in the last column.

Sr. No.	States/Provinces	Districts	Density (people/km ²)	Total number of schools
1	Balochistan	32	18.9	13,279
2	Khyber Pakhtunkhwa	25	238.1	28,178
3	Punjab	36	358.52	52,986
4	Sindh	29	216.02	46,039
5	Islamabad Capital Territory	1	880.8	391
6	Federally Administered Tribal Areas	7 tribal agencies 6 frontier region	116.7	6,011
7	Azad Jammu and Kashmir	10	258	5,985
8	Gilgit-Baltistan	10	24.8	1,275

Source: Pakistan Bureau of statistics (2017)

Baluchistan is the largest province in terms of the area followed by Punjab, Sindh, and Khyber Pakhtunkhwa (KPK). However, the population of Punjab is the highest among the four provinces. The population density is the highest in the Islamabad Capital Territory, with an area of 906 square kilometers, as there are many migrants from other areas to access the quality

⁹ Due to the unavailability of data, 44 districts are dropped from the sample.

education and higher job opportunities available there¹⁰. Approximately 91 percent of the total schools lie in the four provinces, and 9 percent of schools are in the Islamabad Capital territory, tribal areas, Azad Jammu and Kashmir and Gilgit-Baltistan.

Previous literature can be divided based on studies that discuss the output that is used in the education sector. Most commonly number of graduates (enrolment), average test score in different subjects and passing rate is used at individual student and institution level to measure efficiencies (Chen, 2015; Cheng, 2011; Elizabeth M. grennan, 2016; Foundation et al., 1999; Makri-Botsari, 2015; Mayston, 2003; Mintz & Tal, 2013; Ponjuan & Education, 2005; Weekly & Weekly, 2016). However, most policymakers are more interested in the quality of the educational outcome. On the other hand, measures like enrolment and passing rate only provide information regarding the quantity of educational output rather than the quality. Therefore, most studies in educational efficiency agree on using the average test score as a better measure of educational output. In this study, panel data for the year 2013-15 is collected for the selected districts using the published data sources. Data on the output variable is taken from the report of the District Education ranking published by Alif Aliaan. However, the calculations of these output variables are based on the data published by the National Education Management Information System (NEMIS) and Annual Status of Education Report (ASER) for the panel under observation.

The literature on efficiency in education can also be divided based on four different categories based on the input variables that may be used at a different level of study. i.e., individual level, institution level, family-related, and community-related factors that may have an impact on the output. For the institutional level analysis, physical resources like teaching material and textbook, library, laboratory, number of classrooms, transport and other facilities

¹⁰ Pakistan Bureau of Statistics (2017)

are commonly considered (Banker, Rajiv D ; Natranjan, 2008; Davutyan et al., 2010; Carla Haelermans & Ruggiero, 2013; Houck et al., 2010; Z. Hussain et al., 2015; Johnes, Geraint; johnes, 2009; G. Johnes & Ruggiero, 2017; Naper, 2010; Wössmann, 2007). Further, not only the role of human capital, but their quality is also considered by including the indicators like teacher qualification, year of experience, teacher training and teachers' attendance is also considered contributing factor in calculation efficiency. However, this study is using the educational institutional variables aggregated at the district level. Data on the input variables are collected from Pakistan Educational Atlas published by the Ministry of Federal Education and Professional Training.

The data on the uncontrollable environmental factor for each province is taken from the Provincial Development Statistics. Due to the unavailability of the data on the private schools, this study is only considering the data on input and output variables of primary public schools aggregated at the district level (see Table 3.2 and 3.3).

The data used in this study is taken from various data sources like Pakistan Education Statistics, District Education Profile, Pakistan Education Atlas, National Education Management Information System (NEMIS) and Academy of Educational Planning and Management (AEPM). Additionally, some data have been taken from the Sustainable Development Policy Institute (SDPI), Alif Ailaan, Annual Status of Education Report (ASER), and Pakistan Social and Living Standards Measurement Survey (PSLM). As discussed in literature data combined from many sources can add inconsistency in the results. However, only secondary data is used in this essay, which is available at district level. In addition the Almost all the data sources i.e. ASER, PSLM and NEMIS follow the same 2 stage stratified sampling design with some stylized differences in the sampling frame and in strategy.

Table 3. 2: Input/ Output Variables and Data Sources

Input/output variables used in this study are presented in this table, along with detailed description. The data sources and the years for which data is being using is also presented.

Variable	Description	Years	Source
Input Variables			
Pupil-Teacher ratio (Primary school)	It is the ratio between the total number of students and teachers—the average number of students per teacher.	2013-2016	Pakistan Educational Atlas
Teacher/school ratio	The total number of teachers available per school	2013-2016	Pakistan Educational Atlas
Size (pupil/classroom ratio)	It is the ratio between the total number of students and the total number of rooms, i.e., average class size	2013-2016	Pakistan Educational Atlas
Classroom/school ratio	The average number of classrooms available in each school at the primary level.	2013-2016	Pakistan Educational Atlas
Infrastructure score	It represents the percentage of schools with drinking water, electricity, latrine, and boundary wall facility.	2013-2016	Pakistan Educational Atlas
Output variables			
Learning score	The learning score is a weighted average of the literacy rate of the population age 10 and above and percentage of class 5 students who can read in Urdu, English, and can perform a two-digit division. Equal weights are given to these 2 indicators.	2013-2016	Alif Aliaan
Retention score	Retention scoress is the proportion of children enrolled in class 1 who can reach Class 5	2013-2016	NEMIS

Table 3. 3: Control Variables

This table shows the set of controlled variables considered for determining the reason for change in the district level performance.

Variable	Description	Source
Number of Institution	The total number of public schools.	Provincial Development statistics
Literacy rate	It shows that the adult literacy rate of age 15+ year and above, who has the essential skill of reading, writing and numeracy.	PSLM (2014-15)
Population density	Total area divided by the total population in the area	Provincial Development statistics
HDI	Geometric mean of Health Index, education Index and Living Standard Index	UNDP Report (2017)
Immunization rate	The percentage of the children aged between 12 to 23 months who have been fully immunized.	PSLM (2014-15)
Satisfaction with health facility	Households that lack access to quality healthcare Facility	PSLM (2014-15)
Mean years of schooling	Lifetime education of Adult	PSLM (2014-15)
Expected years of schooling	Number of years a child is expected to spend in school based on current enrolment rates.	PSLM (2014-15)
Living standards	Taken from the Multidimensional Poverty Index: Electricity Drinking water Sanitation Infrastructure Household Fuel, Household assets	PSLM (2014-15)

3.4.1 Descriptive Statistics

Descriptive statistics estimate for input/output variables at the district level are presented in Table 3.4. In the case of education, there are multiple outcomes given the multiple-input. This study considers learning and retention scores amongst the many possible educational outcomes to measure the performance of the selected districts. Large variations in the average learning score can be observed across the four regions. Punjab has the highest mean learning score amongst the regions (60) followed by KPK (45), Sindh (35), and Baluchistan (32).

Retention score based on the enrollment is also used in literature to evaluate the performance of the education system. Retention score is defined as the proportion of students enrolled in class 1 who can reach class 5¹¹. Alternatively, it is also considered as the indicator of students' achievement and experience during the year. Thus, a positive and increasing

¹¹ As defined by the National Education Management Information System (NEMIS), which is the primary data source for retention score.

retention score is the indicator of the current environment in the educational institution that is a contribution towards the student's success indicated through a high learning score (Bingham & Solverson, 2016). We can observe that the institutional environment is more favorable for learning in KPK as the retention score is highest amongst the four regions, i.e., 65, followed by Punjab (59). However, the institutional learning environment seems unfavorable in Sindh and Baluchistan, which is indicated by its lower average retention score (see Table 3.4). Therefore, a retention rate below the mean retentions is the indication that there is room for improvement in the overall learning environment, and thus the policymakers should focus more on it¹². Further, student enrolment can be improved by re-engaging the dropout students in the education system. Despite the recognition of the issue, there appeared to be few concert strategies that exit to reduce the drop-out and increase improvement enrolment (Ahmad, Rauf, Rashid, Ur Rehman, & Salam, 2013).

Table 3.4 shows that on average, one teacher is available for every 31 pupils in Baluchistan, 45 pupils in KPK, 40 in Punjab, and 31 in Sindh. The teacher school ratio (TSR) is 3 in the case of Punjab and KPK, i.e., on average, 3 teachers are available in each primary school in a district. The average teacher school ratio is the lowest in the case of Baluchistan, i.e., 1 with a standard deviation of 1. Further, the class school ratio (CER) is the same for Punjab and KPK, i.e., on average, 3 classrooms per school; however, the pupil class ratio is the highest in KPK (44) as compared to Punjab (37). Moreover, the infrastructure index, which shows the availability of the necessities in school, is lowest Baluchistan (25) and Sindh (47), which could be the reason of the lowest retention score in these provinces. Descriptive statistics for the primary school panel data is evident that Pakistan has a diverse education sector, and

¹² Annual Status of Education Report (ASER)- Pakistan (2018)

large variations can be seen between the student performance, retention score, and the different input levels (Table 3.4).

Table 3. 4 : Descriptive Statistics for Output Variables, 2013-16

This table shows the descriptive statistics of the input and output variables used. The data of all these variables is presented based on regional divisions.

Region		Variables	Mean	Std Dev	Min	Max
Baluchistan	Output	Learning Score	32	15	8	70
		Retention Score	37	17	8	78
	Input	Pupil Teacher ratio (PTR)	31	9	16	54
		Teacher School Ratio (TSR)	1	1	1	4
		Pupil Class ratio (PCR)	27	8	13	51
		Class School ratio (CER)	2	1	1	4
Infrastructure	25	8	5	44		
Khyber Pakhtunkhwa (KPK)	Output	Learning Score	45	11	25	67
		Retention Score	65	18	18	96
	Input	Pupil Teacher ratio (PTR)	45	8	30	62
		Teacher School Ratio (TSR)	3	1	1	5
		Pupil Class ratio (PCR)	44	11	15	74
		Class School ratio (CER)	3	1	2	6
Infrastructure	71	17	23	96		
Punjab	Output	Learning Score	60	9	11	76
		Retention Score	59	18	18	95
	Input	Pupil Teacher ratio (PTR)	40	7	23	56
		Teacher School Ratio (TSR)	3	1	2	5
		Pupil Class ratio (PCR)	37	7	18	53
		Class School ratio (CER)	3	1	2	4
Infrastructure	88	10	42	96		
Sindh	Output	Learning Score	35	9	17	68
		Retention Score	47	16	15	77
	Input	Pupil Teacher ratio (PTR)	31	6	20	47
		Teacher School Ratio (TSR)	2	1	1	6
		Pupil Class ratio (PCR)	35	10	22	66
		Class School ratio (CER)	2	1	1	5
Infrastructure	47	14	19	72		
Full Sample	Output	Learning Score	46	15	8	76
		Retention Score	52	20	8	96
	Input	Pupil Teacher ratio (PTR)	37	9	16	62
		Teacher School Ratio (TSR)	2	1	1	6
		Pupil Class ratio (PCR)	36	11	13	74
		Class School ratio (CER)	2	1	1	6
Infrastructure	61	26	5	96		

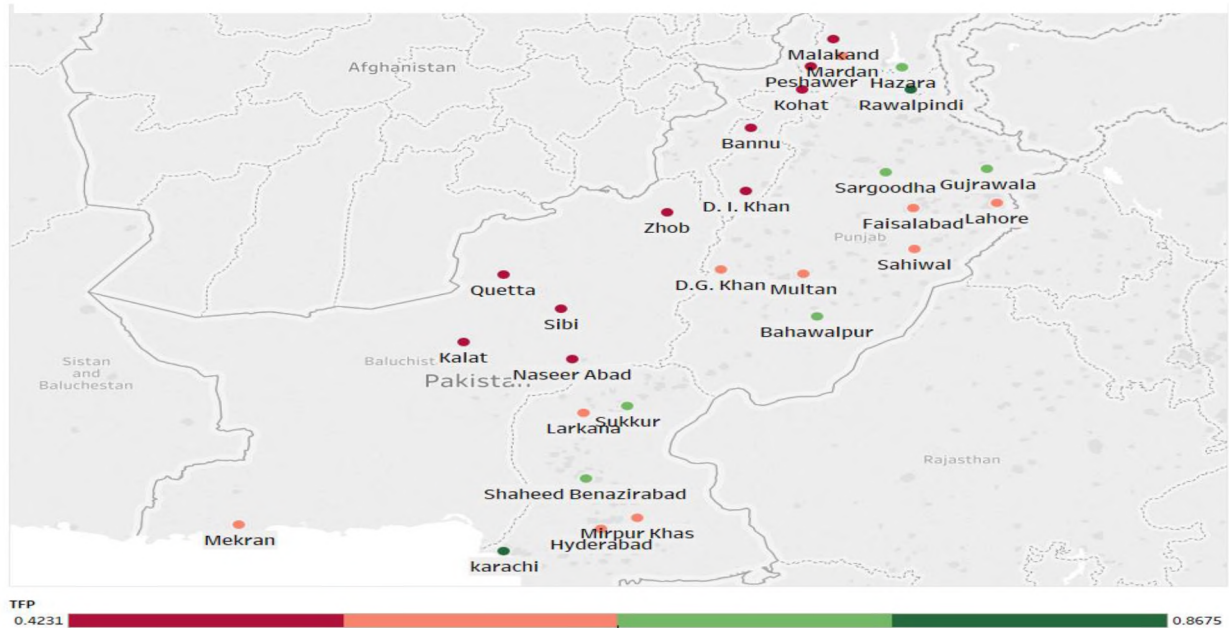
3.4.2 Total factor Productivity across the regions

Figure 3.2 shows the average TFP of all the divisions of four provinces, thus help to identify the relative performance of divisions across the regions. The dark green color indicators the districts with the highest productivity across the country. Low productivity is shown in red color. It can be observed that the majority of high performing districts are located in the province of Punjab.

Within country differences in the level of productivity are large, which can be due to differences in the regional income, population, administration, resources, culture, institutional quality, and geographical conditions (Holmes-Smith, 2006). Thus, the regional heterogeneity can be controlled by calculating the regional TFP. Thus, this study complements the earlier literature by considering the spatial dimensions as an important factor behind the regional differences in the TFP. Thus, this implies that the regional policies should focus more on facilities and transferring knowledge across the district. More specifically, policymakers should focus more on the efficient utilization of the existing resources by exploring economies of scale and scope (McCann & Ortega-Argilés, 2015).

Figure 3. 2 :Annual Average TFP at District Level (2013-16)

Figure shows the Total Factor Productivity of the selected districts. The district shown in green are the high performing ones, whereas the districts in red are the one with lowest total factor productivity.



4.1. Primary School Productivity and Efficiency Level

Table 3.5 presents the primary school’s productivity, efficiency level, and growth rate for all the divisions in 2013 and 2016. These figures are calculated using the Fare-Primont Index, assuming that all the primary schools have a variable return to scale (VRS). Division Rawalpindi has the highest productivity level of 81.3 percent and 78 percent in both the years, which is approximately 45.1 percent and 30 percent more productive than the overall average. The most productive schools lie in Punjab provinces like Rawalpindi, Bahawalpur, Sargodha, and Lahore. The least productive divisions belong to the Baluchistan division, including Quetta, Kalat, Zhab, and Mekran. Particularly, if we consider the Quetta division, it can be seen that it considers of five districts: Chaghi, Killa Abdullah, Noshki, Pishin, and Quetta. Amongst these districts, Killa Abdullah, Pishin, Noshkil is the lowest-performing, and Chaghi

and Quetta show a high TFP¹³. The Chaghi and Quetta are considered urban area with a dense population, further, being the capital city of the province, the performance is also high.

Output oriented efficiency estimates reported in Table 3.5 shows that most of the divisions the technical efficiency and mix efficiency estimates are generally high; however, only a few are fully efficient. It can also be observed that for these low performing divisions the mix efficiency is higher¹⁴ than the technical efficiency D. I Khan (ME 0.976 and TE 0.573), Kalat (ME 0.973 and TE 0.726) and Quetta (ME 0.987 and TE 0.783), which is an indicator that to improve the school performance technical efficiency should be improved. For which the government should focus more on teacher training and skill development. Educational spending has never been more than 2.3 percent of GDP¹⁵, out of which, on average, 7 percent is spent on primary education. Approximately an average of 97 percent of the total budget is spent on the recurring expenditure that mostly constitutes salary expenses from 2013-16, and the rest is spent on the development¹⁶.

The estimated growth rates of TFP and its components are also reported in table 5. The average annual growth rate for TFP between periods 2016 and 2013 can be calculated as $\Delta TFP = (TFP_{2016}/TFP_{2013})^{\frac{1}{4}} - 1$. For example, the TFP growth rate for Kalat division for the period of 2013-16 is $\Delta TFP = (0.412/0.376)^{\frac{1}{4}} - 1 = 0.023$ or 2.32 percent. Similarly, the annual average growth rate of OME can also be calculated for Kalat as $\Delta OME = (0.973/0.940)^{\frac{1}{4}} - 1 = 0.008$ or 0.86 percent. More specifically, a 2.32 percent rate of growth in TFP of Kalat is due to 0.016 percent growth in TFP*, 0.77 percent growth in OTE, 0.86 percent growth in OME, and negative growth of 0.83 percent in ROSE. Further, the total factor productivity of 65 percent of the divisions showed positive

¹³ School district TFP and efficiency levels are in the appendix.

¹⁴ The mix efficiency level is high but it's still inefficient.

¹⁵ Pakistan Economic survey, 2017-18. The educational expenditure as percentage of GDP was 2.1, 2.2, 2.2 and 2.3 in 2012-13, 2013-14, 2014-15 and 2015-16, respectively.

¹⁶ Financing in Education Sector (2018)

growth over time, and 35 percent showed negative growth¹⁷. However, although the Rawalpindi division shows a negative growth rate over the four years, TFP was still the highest in 2016. The highest growth in TFP was observed in Karachi. Bannu, Quetta, Kalat, and D.I. Khan are amongst the division, which shows a low technical efficiency. However, positive growth can be observed for Bannu, Kalat, and Quetta over the four years (9.34 percent, 2.87 percent, and 0.77 percent), whereas the overall position deteriorated for D. I. Khan is indicated by a negative growth rate of 5.24 percent.

The interesting feature of the estimates of the annual average growth rate is that they are additive, i.e., the growth in the TFP is the sum of the growth in TFP* and the efficiency growth. It can be seen that the annual average growth rate of TFP of Kalat from 2013 and 2016 is negative 0.0232, thus $\Delta TFP = \Delta TFP^* + \Delta OTE + \Delta OSME = \Delta TFP^* + \Delta OTE + \Delta OME + \Delta ROSE = 0.0150 + 0.0077 + 0.0086 - 0.0083 = 0.0232$ or 2.32 percent. The annual average growth rate calculated using the Fare Paramount index reported in table 5 is both multiplicatively and additively complete, so it can also be calculated using arithmetic averages.

To make an indirect comparison of the output mix efficiency between different divisions, we can compute the transitive Fare Prominent Index for Lahore, Quetta, and Peshawar. The selected three-division is the capital of three provinces, i.e., Punjab, Baluchistan, and KPK. Such comparison is to illustrate the regional differences in the efficiency level. It can be seen that the change in OME of Lahore in 2016 compared to 2013 was 7 percent lower than Quetta¹⁸, whereas the change in OME of Quetta over the same period was 11.1 percent higher than that of Peshawar¹⁹. Through the transitivity axiom, we can also

¹⁷ Constant average percentage Growth rate is calculated by following Christopher J. O'Donnell's (2018), "Productivity and Efficiency Analysis: An Economic Approach to Measuring and Explaining Managerial Performance", pp. 398

¹⁸ $\Delta OME_{Lahore}^{2016} / \Delta OME_{Quetta}^{2016} = (OME_{Lahore}^{2016} / OME_{Lahore}^{2013}) / (OME_{Quetta}^{2016} / OME_{Quetta}^{2013}) = (1.002 / 1.078) = 0.930$

¹⁹ $\Delta OME_{Quetta}^{2016} / \Delta OME_{Peshawar}^{2016} = (OME_{Quetta}^{2016} / OME_{Quetta}^{2013}) / (OME_{Peshawar}^{2016} / OME_{Peshawar}^{2013}) = (1.078 / 0.970) = 1.111$

compare the OME of Lahore to Peshawar via Quetta. It implies that the change in OME of Lahore is 3.3 percent higher than that of Peshawar²⁰.

²⁰ $\Delta OME_{Lahore}^{2016} / \Delta OME_{Peshawar}^{2016} = (\Delta OME_{Lahore}^{2016} / \Delta OME_{Quetta}^{2016}) * (\Delta OME_{Quetta}^{2016} / \Delta OME_{Peshawar}^{2016}) = (0.930) * (1.111) = 1.033$

Table 3. 5: Annual Geometric Rate of Total Factor Productivity and its Components

This table shows the rate of growth over the four years for TFP, OTE, OME,ROSE and OSME. Geometric means of regional districts are presented at the division level.

Obs	Divisions	TFP			OTE			OME			ROSE			OSME		
		2013	2016	Δ	2013	2016	Δ	2013	2016	Δ	2013	2016	Δ	2013	2016	Δ
1	KALAT	0.376	0.412	2.32	0.704	0.726	0.77	0.940	0.973	0.86	0.784	0.758	-0.83	0.737	0.738	0.03
2	MEKRAN	0.475	0.642	7.82	0.976	1.000	0.62	0.998	1.000	0.04	0.672	0.834	5.52	0.671	0.834	5.56
3	NASEER ABAD	0.519	0.606	3.95	0.972	1.000	0.71	0.917	0.931	0.38	0.804	0.846	1.30	0.737	0.788	1.69
4	QUETTA	0.370	0.448	4.89	0.700	0.783	2.87	0.869	0.987	3.23	0.840	0.753	-2.69	0.730	0.743	0.45
5	SIBI	0.521	0.502	-0.95	1.000	1.000	0.00	1.000	0.974	-0.65	0.719	0.669	-1.78	0.719	0.652	-2.41
6	ZHOB	0.399	0.491	5.33	0.783	0.973	5.56	0.913	0.994	2.17	0.769	0.659	-3.79	0.702	0.656	-1.70
7	BANNU	0.494	0.555	2.93	0.672	0.961	9.34	0.971	0.866	-2.83	0.834	0.803	-0.94	0.809	0.695	-3.74
8	D. I. KHAN	0.496	0.424	-3.85	0.711	0.573	-5.24	0.923	0.976	1.39	0.833	0.913	2.33	0.769	0.891	3.76
9	HAZARA	0.629	0.656	1.06	1.000	0.946	-1.38	0.986	0.995	0.22	0.702	0.839	4.56	0.693	0.835	4.79
10	KOHAT	0.533	0.541	0.35	0.775	0.908	4.02	0.936	0.876	-1.63	0.810	0.819	0.29	0.757	0.717	-1.35
11	MALAKAND	0.567	0.439	-6.18	0.906	0.805	-2.91	0.944	0.879	-1.77	0.729	0.746	0.59	0.689	0.657	-1.19
12	MARDAN	0.601	0.610	0.39	0.915	0.988	1.92	0.994	0.952	-1.07	0.727	0.781	1.82	0.722	0.744	0.72
13	PESHAWAR	0.507	0.531	1.16	0.795	0.851	1.72	0.982	0.964	-0.45	0.715	0.779	2.16	0.703	0.752	1.70
14	BAHAWALPUR	0.755	0.747	-0.27	0.929	1.000	1.86	0.976	1.000	0.60	0.921	0.826	-2.69	0.899	0.826	-2.10
15	D.G. KHAN	0.648	0.606	-1.65	0.925	0.932	0.20	0.988	0.991	0.08	0.784	0.725	-1.94	0.775	0.719	-1.86
16	FAISALABAD	0.602	0.617	0.62	0.977	0.930	-1.22	0.923	0.972	1.30	0.738	0.754	0.55	0.681	0.733	1.85
17	GUJRANWALA	0.699	0.672	-1.01	0.954	0.953	-0.03	0.963	0.939	-0.62	0.842	0.829	-0.37	0.811	0.779	-0.99
18	LAHORE	0.670	0.649	-0.81	0.950	0.951	0.01	0.999	0.974	-0.62	0.781	0.774	-0.22	0.780	0.754	-0.84
19	MULTAN	0.616	0.593	-0.94	0.866	0.831	-1.01	0.962	0.977	0.38	0.817	0.807	-0.32	0.786	0.788	0.06
20	RAWALPINDI	0.813	0.780	-1.02	0.965	0.992	0.70	0.998	0.976	-0.56	0.933	0.890	-1.17	0.931	0.869	-1.72
21	SAHIWAL	0.627	0.617	-0.41	0.872	0.861	-0.32	0.987	0.991	0.10	0.806	0.799	-0.21	0.795	0.791	-0.11
22	SARGODHA	0.673	0.687	0.53	0.867	0.972	2.89	0.986	0.999	0.33	0.870	0.782	-2.64	0.858	0.781	-2.31
23	HYDERABAD	0.539	0.625	3.79	0.929	0.915	-0.37	0.980	0.972	-0.21	0.866	0.921	1.54	0.849	0.895	1.33
24	KARACHI	0.529	0.763	9.59	1.000	1.000	0.00	1.000	1.000	0.00	0.775	1.000	6.59	0.775	1.000	6.59
25	LARKANA	0.506	0.534	1.32	0.898	0.798	-2.90	0.925	0.944	0.50	0.892	0.928	0.98	0.825	0.876	1.49
26	MIRPUR KHAS	0.487	0.599	5.31	0.865	0.910	1.27	0.981	0.978	-0.07	0.841	0.882	1.20	0.825	0.863	1.13
27	SHAHEED BENAZIRABAD	0.606	0.722	4.48	0.933	1.000	1.74	0.990	0.969	-0.52	0.960	0.976	0.41	0.950	0.946	-0.11
28	SUKKUR	0.574	0.676	4.14	0.941	0.991	1.30	0.964	0.937	-0.69	0.927	0.952	0.68	0.893	0.893	-0.01
	Geometric Mean	0.56	0.60	1.53	0.88	0.91	0.79	0.96	0.96	0.00	0.81	0.82	0.39	0.78	0.79	0.38
	Min	0.37	0.41	-6.18	0.67	0.57	-5.24	0.87	0.87	-2.83	0.67	0.66	-3.79	0.67	0.65	-3.74
	Max	0.81	0.78	9.59	1.00	1.00	9.34	1.00	1.00	3.23	0.96	1.00	6.59	0.95	1.00	6.59
	Efficient school divisions				3	6		5	4		0	1		0	1	

3.4.3 Annual Average Indexes of Changes of Total Factor Productivity and its Components

The change indices are obtained by dividing all the values of the district each year, considering the Awaran 2013 as a base for the rest of the districts. The geometric mean of change is then represented for each division: for instance, the technical efficiency change of each division is the geometric mean of four years (2013-16) values of technical change of all the divisions. The resultant change indices are represented in table 3.6. The value of a change index above one represents the improvement of development in the particular division, whereas the value equal to 1 represents the stagnation. An index value above 1 is a representation of improvement in a division. Many studies show that technical change has a significant effect on school productivity and the economic development of the country (Taylor, Grosskopf, & Hayes, 2016). In another study by Lu *et al.* (2016), he examined the socio-economic efficiency and technology development and found that technology is the critical driving force for development. When all the division are taken together, the selected sample experience an improvement of 50.8 percent in the TFP over the period 2013-2016, mostly due to efficiency improvement (47.2 percent), while the technology change index is 1.024 representing a 2.43 percent improvement in the technological change for the same period. Thus, technological change is minimal in the selected period, suggesting that the government should evaluate the technological development in the education sector, and more resources should be utilized in technological improvement.

It can be seen from Table 3.6 that there is a large variation in the TFP change of all the divisions ranging from 1.160 to 2.436. The results also show that for all the divisions, the change is efficiency improvement is greater than the improvement in the technological change. The overall improvement in the educational performance is due to the policy change in 2012-13, according to which a national action plan was developed so that the educational related Millennium

Development Goals (MDGs) till 2015-16 can be achieved. Results also indicate that during 2013-2016, all the divisions showed on average TFP progress. However, a small increase was observed for Larkana (16 percent), Malakand (16.7 percent), and D.I Khan (16.9 percent), while a visibly large improvement can be seen in division Rawalpindi (143.6 percent) and Karachi (111.8 percent). As the change in efficiency component is the major component in improvignt in the TFP, how, eve'r its worth mentioning that the magnitude of change in the components of efficiency does not show the same pattern for all the regions. For example, the 37 percent annual average increase in the TFPE in the Rawalpindi division is due to a 30 percent improvement in technical efficiency, 22 percent due to mix efficiency, and 48 percent due to residual scale efficiency. Therefore, for the Rawalpindi amongst the known factor, change in technical efficiency is more relevant. However, if we consider Larkana, the 13 percent increase in TFPE can be explained by a 2 percent deterioration in the technical efficiency, a 15.3 percent improvement in the mix efficiency, and a 0.2 percent increase in the residual scale efficiency. In case of Larkana division mix efficiency is more relevant in explaining 16 percent TFP improvement ($\Delta TFP = \Delta Tech \times \Delta OTE \times \Delta OSME = \Delta Tech \times \Delta OTE \times \Delta OME \times \Delta ROSE = 1.024 \times 0.980 \times 1.153 \times 1.002 = 1.160$).

Despite the importance of the figures which are explaining the reason for the annual average change, it explains litter about the regional differences. Therefore, it is important to take into account the cross-regional differences. The efficiency results show that the divisions that tend to cluster on the lower end belong to the Sindh (e.g., Larkana) and Khyber Pukhtum Khaw province (e.g., Makakand, D.I Khan). At the same time, the majority of high performing divisions belong to Punjab province (e.g., Rawalpindi), except for the Karachi division that belongs to Sindh. Further, insights into changes can be obtained by analysis of the district-level data²¹. Overall, the

²¹ See appendix

estimated changes in the technical efficiency and the mix-efficiency show that mix efficiency has been the major driver of change in TFPE for the majority of the divisions.

Table 3. 6: Annual aggregated Indexes of changes of total factor Productivity and its Components

Obs	Division	dTFP	dTFPE	dOTE	dOME	dROSE	dOSME
1	BAHAWALPUR	1.707	1.666	1.241	1.171	1.146	1.342
2	BANNU	1.410	1.377	1.051	1.201	1.090	1.310
3	D. I. KHAN	1.169	1.141	0.830	1.225	1.123	1.376
4	D.G. KHAN	1.243	1.214	1.051	1.129	1.023	1.155
5	FAISALABAD	1.618	1.580	1.217	1.206	1.076	1.297
6	GUJRANWALA	1.879	1.834	1.245	1.206	1.222	1.474
7	HAZARA	1.584	1.546	1.152	1.210	1.109	1.342
8	HYDERABAD	1.351	1.319	0.984	1.186	1.130	1.341
9	KALAT	1.280	1.249	1.020	1.144	1.071	1.225
10	KARACHI	2.118	2.067	1.359	1.213	1.255	1.522
11	KOHAT	1.334	1.303	1.099	1.126	1.053	1.186
12	LAHORE	1.679	1.639	1.251	1.182	1.109	1.311
13	LARKANA	1.160	1.132	0.980	1.153	1.002	1.155
14	MALAKAND	1.167	1.139	1.110	1.124	0.913	1.026
15	MARDAN	1.481	1.446	1.193	1.212	1.001	1.212
16	MEKRAK	1.669	1.629	1.341	1.186	1.025	1.215
17	MIRPUR KHAS	1.360	1.327	1.066	1.219	1.021	1.245
18	MULTAN	1.497	1.461	1.141	1.127	1.136	1.281
19	NASEER ABAD	1.618	1.580	1.309	1.196	1.010	1.207
20	PESHAWAR	1.241	1.212	1.036	1.208	0.969	1.170
21	QUETTA	1.361	1.329	0.982	1.130	1.198	1.353
22	RAWALPINDI	2.436	2.378	1.309	1.221	1.487	1.816
23	SAHIWAL	1.419	1.385	1.090	1.195	1.063	1.271
24	SARGODHA	1.769	1.727	1.174	1.203	1.222	1.471
25	SHAHEED BENAZIRABAD	1.622	1.583	1.135	1.158	1.204	1.395
26	SIBI	1.649	1.610	1.359	1.247	0.950	1.185
27	SUKKUR	1.496	1.460	1.047	1.201	1.161	1.394
28	ZHOB	1.565	1.528	1.248	1.223	1.000	1.224
	Geometric Mean	1.508	1.472	1.136	1.185	1.093	1.296
	Min	1.160	1.132	0.830	1.124	0.913	1.026
	Max	2.436	2.378	1.359	1.247	1.487	1.816

3.4.4 Frequency Distribution of Efficiency Level

Table 3.7 shows the detailed frequency distribution for the selected type of efficiencies. The technical efficiency score of 25 percent of the districts lies in the interval of 95 percent and above.

Out of a total of 112, only 13 districts, are fully efficient. Kharan, Killa, Saifullah, Kohlu, Musakhail, Sibi, Ziarat, Chitral, Chakwal, Rawalpindi, and Karachi are amongst the highest performing regions. They are fully efficient simply means that the district has optimally used the resources and reached its full capacity. Higher productivity frontier can be attained; however, additional resources are needed.

Further, it also indicates that to increase the TFP, a technological shift is required. Approximately 38 percent of the districts lie below the mean value of OTE, indicating that educational policies need to be revisited so that some actions can be taken to reduce the number of underperforming districts. In the case of OSME, only district Chakwal lies in the interval of highest productivity level i.e., 95 percent and above. Again, referring to the fact that Chakwal can achieve the maximum productivity level of 99 percent by using the economies of scale and scope. In case of output mix efficiency, it can be seen that eight districts out of the total shows that they are fully efficient in term of allocation of resource mix, there as 42 percent are in the performance interval of 95 percent and above. Further, 58 percent of the district may change the input mix so that they can also reach a higher productivity level. This analysis is recommending chingnge the allocation of resources within the school district so that higher productivity level can be achieved.

Table 3. 7: Frequency Distribution Table

The table shows the frequency distribution for the districts selected in our study. Its shows that for OTE 25 percent of district lie in the interval of 95 and above. For the scale mix efficiency, only 1 percent of district lie in top tier. Whereas for output mix efficiency 42 percent of the districts lie in the top interval, indicating that they are fully utilizing their input resources and are highly efficient.

OTE			OSME		OME	
Interval	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
0.35-0.40	0	0	1	1	0	0
0.40-0.45	1	1	4	4	0	0
0.45-0.50	0	0	5	4	0	0
0.50-0.55	0	0	10	9	0	0
0.55-0.60	5	4	18	16	0	0
0.60-0.65	3	3	25	22	0	0
0.65-0.70	5	4	20	18	0	0
0.70-0.75	12	11	17	15	0	0
0.75-0.80	17	15	5	4	3	3
0.80-0.85	11	10	5	4	7	6
0.85-0.90	14	13	0	0	16	14
0.90-0.95	16	14	1	1	39	35
0.95-1.00	28	25	1	1	47	42
Total	112	100	112	100	112	100
Mean	0.8301		0.6283		0.9294	
Min	0.4471		0.3473		0.7750	
Max	1.0000		0.9959		1.0000	

3.4.5 Tobit Model: Determents of Change in the Efficiency Level

The landscape of Pakistan provides a potential demographic advantage to some of the districts while other districts have to face critical challenges for providing the jobs and service opportunities. The sustainable development of the country is mainly depending on the policy makers and the society, largely how they take the development process. To measure the district level developmental difference, there are many control variables available in the literature. Like competition, number of educational institutions, neighborhood characteristics, location (rural/urban), mortality rate, crime-violence, employment opportunities, poverty rate, population/district size, immigrants and others (Grosskopf & Moutray, 2000; Grosskopf, Hayes, Taylor, & Weber, 2001;Cordero, Santín, & Sicilia, 2013; Crespo-Cebada, Pedraja-Chaparro, &

Santín, 2014; Grosskopf, Hayes, & Taylor, 2014; CMG Haelermans, 2012; J. Johnes, 2015; De Witte & López-Torres, 2017). However, the three main dimensions that are considered to measure the development of a country includes, education, health and the living standard, which will be used in this section to measure the differences across the district. Therefore, if these areas are developed effectively it can play a major role in ensuring the sustainable development of the economy. In addition to these dimensions, total number of primary schools, population density and location is also considered. The table 3.8 below shows the indicators used to measure the dimension of Human development index.

Other indicators like Multidimensional poverty index can also be considered to explain the regional difference in the performance, however, no significant relationship was observed with the efficiency score, so it was dropped. Further, to measure the population division at district level, Population in MPI Intensity (percent) and Population in MPI Intensity (percent) can be considered, however the correlation between the variable was found to be weak and was dropped from the analysis. The objective is to differentiate between the districts based on socioeconomic and geographic factors, thus a simplified population density measure is used in this section.

Table 3. 8 : Indicators Used to Measure the Dimensions of HDI

Dimensions	Indicators
Health	Immunization rate
	Satisfaction with health facility
Education	Mean years of schooling
	Expected years of schooling
Standard of Living	Living standards from the Multidimensional Poverty Index: Electricity Drinking water Sanitation Infrastructure Household Fuel Household assets

Source: Pakistan National Human Development Report (2017)

Table no. 3.9 shows the Tobit regression results²². The overall model tries to explore the factors explaining the differences in the efficiency score. Model (1) reports the results for the technical efficiency and shows that district level literacy rate and living standard are significant and can explain the variations. The literacy rate has a significant positive effect on the output technical efficiency. Thus, indicating that the literate population is more aware about the efficient use of all the available resources. Further, the living standard is negatively linked to the technical efficiency, indicating that the focus should be more on the development of the soft skill and trainings. Literature stressed that teacher training programs are more critical in this age than ever and the role of good teachers cannot be ignored while integrating technology. Researchers also emphasized that teachers are needed both as the facilitator for students to process the immense knowledge coming towards them and also to evolve as think tanks for societal development.

In Model (2) output-oriented scale mix efficiency is the dependent variable, which is the measure of the maximum total factor productivity that can be achieved by availing the economics of scale and scope. It can be seen that the literacy rate (percent of literate population), education index (expected year of schooling and mean year of schooling) and health index has a significant positive effect on OSME. Thus, health facilities and education is a key indicator to achieve a high level of productivity for the district as a whole. The high OSME can be achieved by improving the health and educational accessibility in the lowest performing districts. Further, the Model (2) shows that population density has significantly negative effect on OSME, however the impact is too small to be considered (Table 3.9).

²² Note: The results are represented in terms of thousands of unit.

Further, the model (3) shows that the output mix efficiency is negatively affected by the living standard (Thieme et al.,2012; Deutsch et al.,2013;Grosskopf et al.,2014; Johnson and Ruggiero; 2014). Health index shows a positive effect on the mix efficiency, thus overall improvement in the health facilities can help in improving the overall productivity/performance of the student that can lead to sustainable development in the society. Overall model shows that district location and total number of primary schools in the district do not have any effect on the district level performance. Further, the results also indicate that the rather than spending money on improving the living standards of the district, the focus should be on providing better health and education facilities through which students can be a valuable part of the work force. Pakistani youth (15-29 years) represent the one third of the total population²³. Therefore, better educational provide can lead to better job opportunities and can play a role in the development and growth. The differences in the results of the three models shows that as the OTE which is a lower level of output, is effected by literacy rate and living standard, however OSME which is the a higher level achieved by reallocating the same resource to achieve a higher output, is thus dependent on additional factors like health index, population density.

²³ Censes, 2017

Table 3. 9: Exploring the Determinants of Change for The Efficiency

Results of the Tobit model are shown in the table below. In model 1, OTE is used as the dependent variable, OSME in model 2 and OME in model (3). Along with the coefficient values, standard errors are shown in brackets and the significance of the results are shown by steric signs.

	Model (1)	Model (2)	Model (3)
VARIABLES	OTE	OSME	OME
Total Primary Schools	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Literacy rate	0.0042*** (0.0016)	0.0058*** (0.0009)	0.0009 (0.0006)
Location (rural)	-0.0032 (0.0433)	-0.0284 (0.0270)	-0.0008 (0.0169)
Population Density	0.0001 (0.0001)	0.0001*** (0.0001)	-0.0001 (0.0001)
Health Index	0.0015 (0.0036)	0.0071*** (0.0022)	0.0026* (0.0014)
Education Index	0.0024 (0.0052)	0.0080** (0.0032)	0.0033 (0.0020)
Living Standard	-0.0015* (0.0008)	-0.0008 (0.0005)	-0.0007** (0.0003)
Constant	0.6165* (0.3133)	-0.0532 (0.1932)	0.7179*** (0.1224)
Sigma	0.1320*** (0.0096)	0.0830*** (0.0056)	0.0519*** (0.0037)
Observations	112	112	112
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

3.5 Conclusion

This study measures the efficiency of districts in Pakistan using non-stochastics estimation method. Total factor productivity was decomposed into its components to get the estimates of efficiency. In the estimation, substantial variation of technical, scale mix and mix efficiency among school districts is observed, with an average efficiency score of 83%, 62% and 92% respectively.

The results also indicate that the single most important variable is the literacy rate that explain the

variation in the efficiency scores across the district. The two stage DEA model indicates that the health and socioeconomic factors have a strong influence on the district level performance.

Improving education in the countries that are still developing, will improve both the growth and the benefits that can be achieved from the improved growth. Thus, nationally and internationally the government has started to invest more in the opportunities and resources that can improve the attainment and outcome in developing countries. This focus is reflected by the increase in the overall enrolment across the country. However, the primary motive is not just to improve the enrolment rather, efforts are needed in terms of improving the quality of education. As the analysis shows that the average learning and retention score is too low for the four the regions of Pakistan, much attention is needed to improve the overall quality of education. It is also evident that the increase in retention score does not guarantee that these students will be part of the work force.

In the past few years, there are many studies which reported that the change in the policies resulted in increased learning outcomes, retention and enrollment. However, we need to reconsider the fact that this sharp increase does not have a significant effect on increasing the overall total factor productivity and efficiency at regional and district level. Further, the analysis in this chapter will help research to find the gap and organize their research based on these findings. The TFP and efficiency level provide a benchmark for the overall performance of each district, where do they stand and how the performance can be improved. The results show that only few district that are operating at the full efficacy level. Whereas the majority are operating, lower than the mean average. Thus, it proves insights into the policy makes that major districts are not utilizing their resource efficiency. The findings also guide the policy makers about the maximum total factor productivity that can be achieved by using the same resources, thus recommending an efficient

resource mix. In addition, the districts with high socioeconomic status can improve their efficacy by better managing the teaching staff and workload for students, adoption of new teaching styles. Districts with low socioeconomic status face more challenges in terms of support at home. In these districts more resources should be allocated towards pre-school programs that can better prepare children for entering school. Activities that may increase greater parent teacher interaction should be encouraged. Further, it is recommended to search in detail the teaching and operating practices of the fully efficient districts and implement the same in underperforming districts. Most of the urban area is operating at their full potential, but the attention is needed in the low performing rural districts. Moreover, the potential to improve is also high in such low performing districts. Further, there is dire need to improve the classroom instruction method i.e., the teaching method. Also, a significant difference in the infrastructure score can be seen for the province, Punjab, confirming it as the indicator that guarantee higher productivity.

The results of the Tobit show that education and health play a significant role in improving the efficiency at the district level. However, living standard affect the overall efficiency score negatively, but the magnitude of change is small. High Population density does play negative role in achieving optimal level of productivity. It can be seen from the results that district location in the urban or rural geography do not have any effect on the efficiency score of the district. The findings of the study suggest that the student's enrolment and retention rate in the district can be improved by providing better educational access and health facilities. Further, the practices of districts with a high efficiency score should be carefully observed and implemented in the underperforming districts.

The major limitation of district level studies is the use of aggregated data. However, there are many earlies studies who used the district level data, but few are found in case of Pakistan.

Aggregation of the inputs and outputs at the district level may have caused any specification errors that have been transmitted while calculating the efficiency score. However, the observations and results are almost consistent with the findings of other similar studies. The limitation of this section also indicated the need for a more comprehensive analysis at the school level, which can help to identify the factors that can explain eventually the difference in the students' performance.

CHAPTER 4

ESSAY 3: STUDENTS PERFORMANCE: THE ROLE OF ABILITY, TIME AND PREFERENTIAL RESOURCE ALLOCATION

4.1 Introduction

In the current era Sustainable, economic development is only possible with investment in human capital. Becker (1962) is the main advocate of the human capital as the main determinant of the growth. According to his theory the value and efficiency of human capital depends on its development. Thus, investment in the human health, job opportunities, training and study programs plays significant role in the human capital development and growth (Browne, 2010). However, most of the recent empirical studies on growth and development focuses more on the educational component. Education enriches the human understanding, improves the quality of life and ultimately it leads to improve the welfare of the society.

Access to quality education is the intellectual right of every child and it was first acknowledged in December 1948 in the Universal Declaration of Human Right (UDHR). Further, it was also stated that not only the education until primary level should be free; additionally the education should focus on personal development, and promotes respect for human beings (UDHR Article 26). Recently, Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs) reinforced the importance of education as the universal right regardless of color, language, race, gender, economic condition and social origin.

Academic institutions specifically School plays the role as the basic unit that provides the formal education to students. A student's time spend at school/collage is a tender memory and a happy experience for most of them. However, the life of a student is not without its rough patches. A student faces many problems during its academic years. Some of them are time management,

financial issues, quality education, homesickness, stress, health issue, difficulty in learning, communication issues, language barriers, school bullying, the relationship between student, teacher, and guardian, guidance issue, high parental expectations, lack of motivation, transportation, lack of facilities, access, and others. Thus, students have to deal with both the personal problem and the problems in schools; however, overcoming these challenges and managing large workloads is part of the learning process (Fook & Sidhu, 2015). Many researchers associated these student-level constraints with their academic performance and efficiency. This current study deals with the most common type of constraints that students face, abilities, time constraints (effort level), and financial resources, the key elements that affect the learning outcomes of education.

Literature from educational psychology for the past decades is focused on the psychological environment that motivates the students to ask questions and develop new creative skills. Further, a supportive environment that motivates the unusual ideas and implements their ideas. Behavioral development as a learning process that teaches the students to learn from their mistakes and learn to decide for themselves (Mumford, Medeiros, & Partlow, 2012; Siswono, 2010; Treffinger, 1995). Further, the classroom learning skills, ability to arrange a number sequence, understanding the lessons taught in class, and processing what they are learning improves the performance. Thus, abilities can be broadly defined as the combinations of different skills and abilities ranging from writing, reading, problem-solving and reasoning skills that form the bases of student's efficiency (Kimani, Kara, & Njagi, 2013; Mumford et al., 2012; Farooq, Chaudhry, Shafiq, & Berhanu, 2011; Engin-Demir, 2009; Mahimuang, 2005; Newell, Shaw, & Simon, 1958).

Recently, student's work ethics/ effort they put into their studies is also investigated as the domain that influences the performance. Developing work ethics and molding student's behavior

so that they enjoy what they are learning rather than considering it a burden. Further, motivating the students to complete their tasks on time and put more time and effort into it (IES National Center for Education Statistics, 2006; Sunderland, 2013; Wintrup, 2017). Now a day's academic institution significantly realizes the value of teaching the students to manage time and developing work habits. Thus, a habit to learn and complete their work daily, preferring work over all other activities. Thus, by allocating their time efficiently, they can perform better. These effort levels are visible through high achievements. Another constrain that is frequently discussed in the literature is the available financial resources. The financial resources that a student receives from its family and the other monetary benefits that he receives also affect his self-esteem and, thus, the performance. Akareem and Hossain (2012) are of the view that besides the student's characteristics, its family's economic background and the status in the society also plays a vital role in the opportunities that a student receives.

Much of the previous literature discussed the determinants that can affect the educational outcome, and the majority of it agreed that the performance depends on the school level resources, family level resources, and the individual attributes. In this study, we measure the educational outcomes/student performance in terms of its efficiency, i.e. how efficiently the available financial resources used to maximize the student's efficiency. Additional, the individual students' attributes are discussed in many studies in case of Pakistan (Alderman, Orazem, & Paterno, 2001; Harlech-Jones, Baig, Sajid, & ur-Rahman, 2005; Niazi & Mace, 2006; Javid, Musaddiq, & Sultan, 2012; Lall, 2012; Khan & Shaikh, 2013) but very few studies discussed the extent to which the constraints that individual student face impact the efficiency. Therefore, this study investigates the extent to which individual student abilities, effort level, and financial resources constrain affects efficiency as a whole. Further, this study identifies and measures the impact of individual

constraints on the overall efficiency of each student. The study measures the efficiency-using two-step Data Envelopment Analysis and Tobit model is used in the second step to investigate the factors that can explain the change in the efficiency level calculated on the first step. Because the government is allocating the resources for educational development and the students are also receiving family level resources, then why the performance of public sector schools is not improving. The question is not to increase the resources, but rather how the available resources can be used effectively to maximize the students' performance. Therefore, there is a need for deeper investigation based on the microdata, the cause of low performance.

4.1.1. Objectives of the Study

This study investigated the individual student attributes specifically, constrains that a student faces in his or her academic years to analyze the cause of a student's low performance. More specifically, different objects that we intend to achieve through this research is

Primary Purpose:

- To identify the technical efficiency of the individual student by using a sophisticated econometric technique called Data Envelopment Analysis (DEA).

Secondary Purposes:

- To investigate the determinants of student-level efficiency
- To examine efficiency level differences across different ethnic groups
- To check whether an efficiency score differs for students with different abilities
- To explore the role of effort level in improving students' performance and efficiency
- To examine the effect of a student's financial resources on its performance

4.1.2. Significance of the Study

Additionally, this study examines the link between ethnicity and efficiency score and aims to provide policymakers with additional information that is required to make decisions regarding resource allocation. Lastly, the research provides guidelines for shaping appropriate educational policies. However, it is very difficult to satisfy the diverse segments of the student population. Though, the results from this study help the policymakers in identifying different segments of the student groups based on their characteristics. Thus, different policies can be implemented based on constraints that these students face. Therefore, it helps policy makers to plan strategies that improve individual efficiencies and productivity, especially in developing countries.

4.1.3 Contribution of the study

This study contributes to existing knowledge to understand the impacts of cognitive, non-cognitive abilities, time, and resource allocation in concerning developing country prospect. This study is the first in terms of developing country perspectives to identify the role of mentioned determinants on the student academic performance overall. In the further it provides insights to policymakers, educators, and governmental body to understand the impact of these determinants on the individual student performance.

4.1.4 Structure of the Essay

Section 1: The introduction section talks about the background of the study, possible potential determinants of the study as well as the available gaps. Student performance in academics is important for the economic, technological, and other sectors in concern to future recruitment. Therefore, the study wants to find out the collective role of these independent parameters on individual student performance.

Section 2: The literature review section did investigate the association of the selected variables on student performance. The three selected variables are ability, time, and resource allocation. Different theoretical frameworks have also been discussed available in the literature about this domain of research as an incremental competence questionnaire, the incremental theory of intelligence, entity theory of intelligence, social-cognitive approach, and self-management approach.

Section3: Methodology session discusses the econometric methodologies that are used for the analysis of the current study. Further, the methods used for the data collection, filling missing data and its processing is also discussed. In this research study, Data Envelopment Analysis is applied for the measurement of student efficiency concerning independent variables.

Section 4: Based on the results obtained from the DEA analysis, the interpretation is carried out to analyze the findings. The observed scenarios are discussed concerning peer-review literature. Further, the efficiency level calculated in the first step is then used and the independent variable and regressed on the factors that can explain the change in the efficiency level. All the findings mentioned, highlight the potential contribution of the research to the available literature.

Section 5: In this section, the key findings which would show the potential impacts of these evaluated parameters are reported.

4.2 Literature Review

Many economic theories discussed in the literature are based on many unrealistic expectations and assumptions about human behavior, but in reality, each individual is different in their attributes and the learning process. Besides other factors discussed in the literature, individual-level efforts and attributes are also considered as the whales to boots success.

Gorbunovs, Kapenieks, and Cakula (2016) consider the role of motivation and self-discipline in facilitating success and goal achievement. There are many indicators used in the literature to measure student's abilities and link them with performance. The indicators used in the literature to measure student performance include standardized test scores, efficiency scores, and grades. Some other studies the outcome of students based on the assignment completed in time, the number of student passes, move to the next grade, and the enrollment rate. Thus the outcome is based on the strategic goals that are set (Morcke, Dornan, & Eika, 2013). However, this study uses efficiency as a tool to assess the performance of students.

The term efficiency can be applied to any field of study, and education is one of them. Educators are always worried about the efficiency of their educational system. However, they believe that efficiency is a worthy goal. But they are worried that their effort to improve educational quality is not enough. Recently, attention has been shifted to the efficiency of government. Efficiency is often referred to as the desire to obtain more results from fewer resources. It is not a phenomenon of yes or no; rather, it is discussed in the relative term. Farrell (1957) states that firm efficiency can be divided into two components, i.e., allocative efficiency and technical efficiency, combine they form economic efficiency. Technical efficiency refers to the firms' ability to transfer the inputs into the maximum achievable level of output (Koopmans, 1951). At the same time, allocative efficiency refers to the ability of a firm to maximize its outcome with the optimal combination of input given its prices. There are different types of efficiencies discussed in the literature like productive efficiency, structural efficiency, scale efficiency, X-Efficiency, and others. However, the main purpose of this study is the calculation of technical efficiency at the student level.

4.2.1. Student's abilities and performance

Every individual has its own set of abilities and skills with which he or she excels in the academic career, but these abilities are not limited. Abilities refer to the capability of an individual to perform a task efficiently. Ability is widely discussed in different domains of psychology, biology, and others (Zhou et al., 2020). Some researchers defined it as the capability to understand a language, intelligence, skill development, and capacity to memorize. First, the ability is divided mainly into two sets of skills; cognitive and non-cognitive. The first one includes intellectual skills, such as identifying, analyzing, and demonstrate knowledge in problem solving. At the same time, non-cognitive skills or psychosocial skills are; social expressivity, social sensitivity, emotional support, perseverance, conscientiousness, conflict management, self-control, openness, neuroticism, agreeableness, and last but not the least motivation (Komarraju, Ramsey, & Rinella, 2013). The role of motivation comes under the premises of the social-cognitive approach and impacts significantly on the performance and success (Logan, Medford, & Hughes, 2011).

This section reviews the studies that discuss abilities and their role in student performance. Williams, Lathers, Smith, Payer, and Volle, (2001), Litzinger et al. (2010), Mayer, (2010), Wüstenberg, Greiff, Vainikainen, and Murphy (2015) discussed the role of problem-solving skills development in professional education. They are of the view that problem-solving skills development is not given much importance in student growth. Thus, stressing on the use of computer-based learning to solve complex problems (Md. Yunus et al., 2006). However, some students are good at one task and bad in the other. Some students can have a better conceptual understanding, but may not be good in implication. In another study by Ferm (2017) investigated that the students with better understanding have better reasoning skills. Incorrect reasoning can lead to common mistakes and, ultimately, the performance of the physics student. However, the

difficulty level varies across subjects; thus, the finding cannot be generalized, and further analysis is needed.

The control of behaviors, reactions, and thoughts to cope up with the environmental changes in a positive way is known as positive self-control, whereas the aggressive reactions or may say behaviors are negative self-control (Miller, Asarta, & Schmidt, 2019). Social expressivity is another non-cognitive ability that helps the individual to communicate, interact and express socially (Férez & Cortés, 2017), whereas social sensitivity the individual becomes sensitive to his or her environment, feelings, thoughts and behaviors of others (Brown, 2017). Emotional support directs the individual about healthy interactions, concern to fellows, compassion, and empathy. Likewise, the conflict management points towards the group activities and the effective management of any conflict in a positive way. The ultimate objective behind conflict management is to enhance the learning and decreasing the negative outcomes of any activity (Conine Jr & Leskin, 2016).

In literature, abilities are considered as a predictor of the student's performance and may say success (Grigorenko & Sternberg, 1997). Researchers believe that both cognitive and non-cognitive abilities play a part in the academic performance of the pupils. Further to this context, it observes that non-cognitive skills are set to control the academic performance more in comparison to the cognitive skills set (Costa & Faria, 2018; Komarraju et al., 2013). Regarding theoretical frameworks, there are many theories available in this domain. Concerning intelligence, two famous theories are on discussion table; entity theory interprets that "intelligence is fixed" or present, whereas the incremental theory interprets it with a developmental learning process and states that "intelligence can be cultivated or improves with the help of effort level." The former theory gives preference to assessment based on fixed skills set where the later theory gives importance to the

goal's learning. The term poor performance in academics describes differently in both frameworks. The entity theory explains the poor performance by the lack of ability while the incremental theory evaluates the poor performance with a little effort level. Overall, both of these theories do not link with the cognitive skill set, but the contrary to this, associated with the self-regulatory mechanism as well as predictions about the academic success of the students (Costa & Faria, 2018).

Concerning psychological, empathy, social skills and abilities, a famous theory known as interpersonal competence is of prime importance. Moreover, theory related to successful social interaction, information gaining, distributing process, feeling, opinions, and attitudes. Simply interpersonal competence performs an important part in various areas of human life or may students. It states about the self-esteem, negative impaired vulnerable competences or and attitudes. Interpersonal competences questionnaire (ICQ) along with its five-factor domain analyze the convergent validity, test-retest reliability, and internal consistency (Giromini et al., 2016).

Likewise, in literature, there is substantial information about the non-cognitive ability, self-control, and its implications on the students' grade and consequent on the task performance. It shows that students with high or positive self-control are usually good at achieving targets on time and getting distinguish the marks, besides it also reported that the students who get a good score on self-control are best in academic performance as well (Tangney, Baumeister, & Boone, 2004).

However, there are some schools of thought which considered that student's performance could not measure entirely based on abilities or skill set. They reported three approaches that played their role in the measurement of student success; 1) cognition-centered, 2) personality-centered, and 3) activity-centered. The first one deals with the cognitive styles, for example, self-consistent, the second one deals introversion and extroversion personality traits of the individuals

which help in getting good grades the last one deals with the learning process (Grigorenko & Sternberg, 1997).

Arif and Saqib (2003) discussed the role of cognitive skills in measuring the quality of education. The results for 50 schools across different districts are discussed in detail in the public, private, and NGO schools. The result shows no significant difference between test scores for public and NGO types of school. However, the outcome of public and private schools showed a wide gap in performance. Thus, the gap is explained in terms of family and school level constraints. Though, only a few indicators explain the individual student level differences like age, sex, attendance, and homework. Therefore, more indicators are needed to explain the differences in individual abilities and their role in educational quality. Further, the differences in the district level attributes are considered in the cross-district comparison.

Few studies related the difference in gender with abilities. The results show that females have an advantage in general intelligence, whereas male students have strong visualization skills. Whereas, the cognitive skills across gender are the same; therefore, other factors may explain the differences. These differences are explained in terms of the order in childbirth, cultural differences that provide more opportunities for the male child (Croson & Gneezy, 2009; ICKES, GESN, & GRAHAM, 2000; Reilly & Neumann, 2013; Schwieren & Sutter, 2008). A study by Jenkins, Brumfitt, and Stackhouse (2015) compared the educational attainment for young students who stammer with national achievement. They found that the educational attainment is significantly and negatively influenced by the stammering, but due to small sample size no near cut conclusion could be made (Fama & French, 2006; Fazzari, Hubbard, & Petersen, 1988; Guiso & Parigi, 1999; Richardson, 2006).

Another issue that is widely discussed in the literature is the measurement issue of both cognitive and non-cognitive skills. There are many measures available in the literature that the cognitive skills, most common of them are the IQ test, achievement test, and the grades in the subjects. Estimation of the cognitive skills can be carried out from the academic test score, SAT, and CGPA. It has been found that there is a positive relationship between test score and cognitive skills, and this positive association interprets academic success. Some researchers reported that non-cognitive skills are linked with contextual or behavior, whereas some evaluated this linked with personality. However, these measures are criticized based on the correlated, but it's practiced. Based on the fact that different types of tests try to measure different cognitive skills (Flynn, 2007; Nisbett et al., 2012).

Further, based on the evidence found in the literature, the achievement is also affected by other factors like effort level, motivation, commitment, and other non-cognitive skills. Almlund, Duckworth, Heckman, & Kautz, (2011), Borghans, Duckworth, Heckman, and Weel, (2008a, 2008b), Borghans, Meijers, & Ter Weel (2008) and Kautz, Heckman, Diris, Weel, & Borghans (2014) focused on constructing different measure that can help in measuring non-cognitive skills. Some of the different measures used to measure non-cognitive abilities are The International Development and Early Learning Assessment (IDELA). Other than the standard variables used to measure the reading, writing, and math skills, IDELA used variables like peer relation, empathy, self-awareness, emotional awareness, and conflict resolution ability to measure non-cognitive.

Another measure developed by Devercelli, Raikes, and Anderson (2015) is the Measuring Early Learning, Quality and Outcomes (MELQO), which assessed the student's outcome based on the teachers/parent's direct assessment, learning approaches used emotional level, reading, writing, math and science skills and the overall infrastructure of the system. In another project

conducted in India by the name of “Room to Read” provided a reading room for different schools. The study was based on two groups of girls’ schools; one is the treated group that is provided with the reading room. Further, the teaching staff provided them with additional time to develop their reading skills, and habit—Randomized Controlled Trial (RCT) methodology used to see the impact of skills provided on achievement. The non-cognitive skills developed was measured based on different tasks provided. The girls took the mirror test to draw different shapes, with an increasing difficulty level. The objective was to test how long the students are willing to complete the task. In another activity, the girls are given a long list of items they should obtain and were encouraged to take help from friends and family. The number of items collected shows the students' effort and willingness to complete a task. The Global Monitoring Report (2015)²⁴ discusses the results of the project and is of their view that 2500 girls in the treated group showed higher achievement as compared to the untreated group.

Many other indicators used to measure non-cognitive like absences, grades, participation in sports, clubs, suspensions, grades, self-control, and others (Jackson, 2012, 2016; Lleras, 2008; Pratt & Cullen, (2000). Some researches criticize the behavioral approaches to life skills and suggested to use self-reported measurement scales (Heckman, Humphries, & Kautz, 2014). However, further research is needed in the area for non-cognitive skill measurement. In today’s era, students need to adopt creative thinking and must acquire complex problem-solving skills. Even if the students can perform, they can lack the background knowledge. Therefore, even after acquiring the desired abilities and skills, the student’s willingness to achieve the desired goal is very important. They thus concluded that some of the researches, as mentioned earlier, supported the role of cognitive abilities with a positive relationship and strong prediction about student

²⁴ <https://www.roomtoread.org/the-latest/measuring-the-effectiveness-of-a-life-skills-education/>

performance. In contrast, some supported non-cognitive abilities in this concern, therefore mixed results are observed in the literature. The findings of this study are an addition to the empirical literature for developing countries that are investigating the role of abilities on student performance.

4.4.2. Effort level and Performance

In addition to the role of ability, allocated time to study and related activities can play an efficacious role in improving student performance thus is used as a proxy to measure the effort level and hardworking attitude. Time management is an important attribute and skill set of the self-management category. It guides the student about efficiently managing time and, consequently, its impacts on student performance. Further, it directs the students about to prioritize that what is most important and what is least, goal setting, ability to organize and then allocate time to each task accordingly (Alias, Noor, Bhkari, & Ariffin, 2019; Ghiasvand, Naderi, Tafreshi, Ahmadi, & Hosseini, 2017). Within the prospect of learning and improvement, researchers considered that time management is essential and helps in getting good grades as well. Effective time management with educational goal setting can help to increase student productivity in both curricular and co-curricular activities (Khan, Zeb, Ahmad, & Ullah, 2019).

Effort level is an indicator that the student is motivated and willing to work efficiently to achieve its desired goals. Even if the student is doing all he can to improve performance, he can face many constrain due to the time he can spend between studying and other activities. Thus, self-regularity, controlling, and monitoring daily actives and the time allocation towards studying are of crucial importance. Greene and Azevedo (2007) are of the view that the students who are more plan and regulate their daily activities have a higher ability to understand complex problems taught at school. In another study by Yumusak, Sungur, and Cakiroglu, (2007), he concludes that students

of biology who have high achievements are those who managed their environment and organizational skills effectively.

A strong positive association is seen between time management and academic performance. The possible instigators, the drivers that promote the time management skill set, are motivation, ability, performance, and self-motivation. Scholars suggest that students should learn time management to achieve excellent results in academics and other aspects of life. Thus, teachers should encourage students to allocate their time between different activities properly and evaluate their performance, as if they can achieve their desired goals or not (Pintrich & Schunk, 2002). There should be training workshops, programs, and seminars in all levels of educational institutes to educate the students about time management skills (Nadinloyi, Hajloo, Garamaleki, & Sadeghi, 2013). Another study concludes that managing time in an efficient way is related to survival and excellence in life (Alias et al., 2019).

Some researchers relate the time constraints while completing an examination or test with the performance (Macher, Paechter, Papousek, & Ruggeri, 2012; Eysenck, Derakshan, Santos, & Calvo, 2007; Dolton, Marcenaro, & Navarro, 2003; Calvo & Eysenck, 1992). However, no solid evidence is found that the increased time in examination improves results. Further, the effect of increased time may have a different impact on different levels of education. In some recent studies, students' work ethics are also used as a proxy for efforts. Students that consider studying as a desired activity rather than a burden and allocate more time to complete their work ought to perform well. Work ethics also relate to self-discipline, i.e., working on a daily base and even on weekends when required (Abbasi & Mir, 2012; Barrouillet, Bernardin, & Camos, 2004; Onwuegbuzie & Seaman, 1995).

Further, work ethics is not an inherent phenomenon, rather, learned behavior from culture, environment, family, and organization (Hopland & Nyhus, 2016; (Kuehn & Landeras, 2014). Thus, to achieve the educational targets, there is a vital need for prioritization of the daily life routines following the academic task and projects. For stable and consistent results, short-term and long-term goal settings, identification of important assignments, planning and preclusion of the deferential attitude as all lead to improving student work quality. Further, in this concern, it reported that efficient time management is negatively correlated with incompetence to task accomplishment, depression and anxiety whereas it is positively correlated with the fulfilment of the pre-planned objectives (Sainz, Ferrero, & Ugidos, 2019). Researchers do agree that there is no exact explanation of time management skill but different authors described it differently (Ghiasvand et al., 2017; Van den Broeck et al., 2020). In one place, it has been mentioned that this skill set is usually based on three features: 1) attitude of managing time effectively, 2) short term scheduling, and 3) long term schedule. Whereas in another study, it has been described as the ability to control the optimal level of stress, depression, and anxiety while at another place it is explained as the organization of activities to achieve the important goals (Adams & Blair, 2019; Sainz et al., 2019).

In comparison to the mentioned time management skillset, that students who do not manage their time effectively suffer from poor academic performance and outcomes (Khan et al., 2019). There many advantages of time management in concern of student performance in both educational careers as well as in practical life, including (Ghiasvand et al., 2017). Some of the factors which are associated with student performance are satisfaction level, quality of outcome with courses which are being taught, level of creativity along with their increased self-efficiency

which all lead towards decreased drop out of students and in other sense improve student performance (Khan et al., 2019).

The literature shows mixed evidence for the impact of work ethics on student performance; however, a study by Abbasi and Mir (2012) in Pakistan shows that work ethics do not assure you good performance; rather school environment and teacher abilities matter more. Thus, students' time spent out of school also has an impact on their attitude and behavior. Time spend with a person that aspires you in an organization, or personal domain can make you feel more confident, empowered, and thus can be responsible for an increased effort. Overall, it can be said that effective time management is a strong predictor of the high level of academic performance with excellent outcomes, both in school life as well as in practical life because it helped the students to give priority to a different task and taught how to select the most important first and less important later. It also teaches them decision making along with selection.

4.2.3. Financial Resources and Performance

Despite the large literature available in the area of education, financial resources have always been discussed as the opportunity of receiving an education; however, very few studies considered the role of financial constraints. The family's role in providing financial resources can never be ignored; however, the cost of schooling can be more than what a family can contribute.

The resource allocation determinant is also used to understand its prediction level, significance, probable correlation positive or negative with the student performance. Reports existed in the literature about this determinant and its influences on academic success (Hanushek, 1997). The findings of his study suggested that there is no significant positive correlation between student

performances with the school resources; the authors also mentioned the existence and link of family inputs in this prospect.

In other research, it has been reported that there is no significant association of resource allocation with academic performance, test scores, and achievements. In this same study in a broader context, the authors reported that there is just a 25 percent significant association of library resources with student performance in mathematics. The current study is conducted on the achievement level in mathematics and art languages. Very little association is found between the complex subject and resource allocation in this subject area (Neal, 2016). In concern to planning strategy, the plan to effectively use the available resources for the accomplishment of success in an academic career is known as resource allocation. Such resources includes energy, knowledge, natural resources, human resources, services, technological resources, financial resources, architecture, transportation, infrastructural and others.

The process of resource allocation is mostly carried out for the enhancement of knowledge, sustainability, production, and productivity. In another study, the authors did focus on financial resources and their role in student performance. They termed this resource as a school-based budget and its importance in the overall education sector and, consequently, on the student academics (Goertz & Stiefel, 1998).

Some scholars reported that it is not clear which factor from demographic (socio-economic prominence and family background) and resources impacts more on the student academic accomplishments (Pan, Rudo, & Smith-Hansen, 2002). At another place, the authors considered effort and time as resources and measured its role in academic performance (Beck & Schmidt, 2018). From all the studies mentioned above, it is found that student performance is positively

associated with financial resources. In some studies, it is found that there is no significant relationship between student performance in arts subjects and with the available library resources. So, the positive, negative, and no associations might be observed because of the different types of cultural and demographic prospects in this world—these mediator's impacts on the resource allocation process and resultantly the academics of the students. Students living in low-income families face underinvestment in their education. The other option that a student can avail of is the scholarship that he receives from governmental and non-governmental agencies. However, financial aid receives can affect the self-esteem of parents and children.

Further, the parental decision about an educational resource that a child may receive also depends on the family size. Many studies found that the larger the family size, the lower is the educational investment each child receive in case of developing countries (Hampden-Thompson, 2013; Kang, 2011; De Haan, 2010; A. L. Booth & Kee, 2009; Booth & Kee, 2009; Calvet, Campbell, & Sodini, 2009; Lu & Treiman, 2008; Teachman, 1987). Li et al. (2008) found no effect of family size with human investment, and it may be because the educational system is well developed in western societies. Whereas, child labour practices and the absence of quality education in public schools prevents the low-income group from investing in education.

Few researchers are of the view that family size is not the core determinant of financial constrain; rather, birth order matters more. The elder child in the family receives more resources than the other siblings. Some researchers also argue that the birth order and the number of years of education are positively correlated with reach other (a Booth & Kee, 2009; A. L. Booth & Kee, 2009; de Haan, 2010; Jæger, 2012). Further, gender-based inequalities in receiving financial resources cannot be ignored, especially in the case of underdeveloped countries (Kugler & Kumar, 2017). Therefore, scarce financial resources, create natural competition between siblings and

preferences for a boy child give them an initial advantage (Garg & Morduch, 1996). Thus, cultural, demographic, and family level characters, jointly determine the educational financing decision.

4.3 Model and Methodology

4.3.1 Theoretical Framework

This section discusses the theoretical framework of the model. This model assumes that the educational outcome of an individual student is associated with institutional and non-institutional input. There is no unique outcome measure used in literature; in this study, we use the total exam score as an aggregate. Further, for a detailed analysis, individual subject's score is used as the outcome. In the first step, we will regress the outcome of an individual student over a set of explanatory variables and calculate the technical efficiency.

As O'Donnell (2008) methodology is the extension of DEA models, requires the non-parametric models, so it is not necessary to specify the functional form to identify the relationship between the outputs and the inputs (Coelli et al. 2005). The total factor productivity level calculated using the inputs and the outputs. The educational production function is represented as follows

$$Q_{sj} = f(A_{sj}, E_{sj}, R_{sj}) \quad (4.1)$$

Where, Q_{sj} Represents the outcome of S_e^{th} student in the j^{th} school. A_{sj} represents the students' abilities (cognitive and life skills) in the sample school, E_{sj} Is the effort level of individual student measured in hours. The set of all the resources available to individual students is represented by R_{sj} . Each student receives the school's resources and as well as the family resources, which will be discussed in detail.

Battese and Coelli (1995) extended the model by using the technical efficiency in the first model and analyzed the factors that can explain the differences in the student's efficiency. The function determined the technical inefficiency effects are defined in its general form as a linear function of educational institutions, family, and individual student factors. An efficiency score level equal to one indicates that the inputs used are fully efficient, and an efficiency score of less than one shows inefficiency. The Tobit regression model is estimated as the dependent variable "technical efficiency" truncates data.

$$Efficiencny_{sj} = \gamma_0 + \gamma_1 school_{sj} + \gamma_2 family_{sj} + \gamma_3 student_{sj} + \varepsilon_{sj} \quad (4.2)$$

The above equations show the efficiency score of s^{th} student in the j^{th} school. The random error term is represented as ε_{sj} Which is identical and independently distributed. Further, γ_i ($i=0 \dots 3$) are the parameters that need to be estimated. The set of school-level resources is represented by the vector "*school*," socioeconomic status of the student's family is represented by vector "*family*," and lastly, the individual student characteristics are represented by the vector "*student*." Thus, this model explains the differences in the efficacy of each student based on these controlled variables.

4.3.2 Data Envelop Analysis (DEA)

To estimate the School Efficiency Maximization, the DEA model is used in many studies in the area of education. Researchers in many applied and fundamental studies used DEA model in making policy-related decisions. Charnes, Cooper, and Rhodes (1979) introduced the DEA model by extending the work of Farrell. This model is estimated in two stages. Firstly, an efficiency score of the student based on input variables is calculated. In the second stage, regression analysis is performed to estimate the relationship between independent variables and the efficiency score. Tobin (1958) regression is used in the majority of the studies that calculated the school's

efficiency. However, some recent studies are of the view that Ordinary Least Square (OLS) is a preferred model. Therefore, the literature shows mixed results for the model selection between OLS and Tobit model. The output-oriented model to calculate efficiency can be represented as

$$\text{Max } Z_0 \quad (4.3)$$

$$\text{s. t. } \sum_{f=1}^F \lambda_f y_{qk} \geq zy_{q0} \quad (4.4)$$

$$k = 1 \dots K; \quad q = 1 \dots Q$$

$$\sum_{k=1}^K \lambda_k x_{fk} \leq x_{f0} \quad (4.5)$$

$$f = 1 \dots F$$

$$\sum_{k=1}^K \lambda_k = 1$$

Here, x_f denotes the f inputs, y_q are the output q , and the k represent the students or the decision-making units. The vector λ represents the weights assigned to each school, whose efficiency is to be maximized. K^{th} student is said to be efficient if $Z_k = 1$, whereas if the $Z_k < 1$ then the school is inefficient. Unlike many other estimation techniques used to measure efficiency, the DEA model works in the situation with multiple inputs and multiple outputs. However, while calculating efficiency, it is of critical importance which inputs and outputs are used. If the most relevant variables are excluded, then the model may get affected by omitting variable biases. According to Cooper *et al.* (2006), the number of DMUs should be three to four times more than the sum of inputs and outputs used in the DEA model. If the sample size selected is small, we can have a problem with the degree of freedom. In a study by Johnes (2004), multicollinearity can also

be an issue in the DEA models. However, other studies show that multicollinearity does not affect the efficiencies much; however, there are still are mixed opinions about these issues (Ertay & Ruan, 2005; Nataraja & Johnson, 2011; P. Smith, 1993, 1997).

Following (O'Donnell 2008), we used the DPIN software to calculate the efficiency score. This software mainly uses the Data envelopment analysis, linear programming model to estimate the total factor productivity and efficiency. The benefit of using this methodology is that it does not require any assumption regarding the competition between the students (DMUs) or students' optimized behavior. Further, all the input quantities and output quantities are aggregated to calculate the productivity index. The total factor productivity (TFP) is decomposed into the components of technical change, technical efficiency, scale efficiency, and mix efficiency.

Thus the output-oriented technical efficiency (OTE_{it}) can be defined as

$$OTE_{it} = \frac{Q_{it}/X_{it}}{\bar{Q}_{it}/X_{it}} = \frac{Q_{it}}{\bar{Q}_{it}} \leq 1 \quad (4.6)$$

Where, \bar{Q}_{it} is the maximum level of aggregate output possible using the x_{it} level input to produce scaler multiplier of q_{it} . The range of efficiency components lie between 0 and 1, i.e., 0 is the lower limit representing the inefficient unit, and 1 represents the full efficiency DMUs that lie on the production possibility frontier. Output oriented scale efficiency can be defined as

$$OSE_{it} = \frac{\bar{Q}_{it}/X_{it}}{\tilde{Q}_{it}/X_{it}} \quad (4.7)$$

Where \tilde{Q}_{it} represents the maximum optimal level of output that can be achieved using the same level of input

O'Donnell, (2008) associated the TFP with economies of scale and scope and defined the Output-oriented Scale Mix Efficiency as ($OSME_{it}$) as the product of Output-oriented Mix Efficiency (OME_{it}) and Residual Output-oriented Scale Efficiency ($ROSE_{it}$). Output Mix efficiency can be represented as

$$OME_{it} = \frac{\bar{Q}_{it}/X_{it}}{\hat{Q}_{it}/X_{it}} = \frac{\bar{Q}_{it}}{\hat{Q}_{it}} \leq 1 \quad (4.8)$$

Where \hat{Q}_{it} is the maximum level of aggregate output that is produced using technically feasible x_{it} and achieved any output vector?

$ROSE_{it}$ can be mathematically represented as below

$$ROSE_{it} = \frac{\hat{Q}_{it}/X_{it}}{TFP_{it}^*} \leq 1 \quad (4.9)$$

where, $TFP_{it}^* = Q(q_{it}^*)/X(x_{it}^*)$ and $ROSE_{it}$ is the component remaining after accounting for the technical and the mix efficiency.

With the help of efficiency measure defined about we can now measure the Total Factor Productivity Efficiency ($TFPE_{it}$) as

$$TFPE_{it} = OTE_{it} \times OSME_{it} \quad (4.10)$$

$$TFPE_{it} = OTE_{it} \times OME_{it} \times ROSE_{it} \quad (4.11)$$

$$TFPI_{hs,it} = \left(\frac{TFP_{it}^*}{TFP_{hs}^*} \right) \times \left(\frac{OTE_{it}}{OTE_{hs}} \right) \times \left(\frac{OME_{it}}{OME_{hs}} \right) \times \left(\frac{ROSE_{it}}{ROSE_{hs}} \right) \quad (4.12)$$

Equation (11) shows the efficiency measures of i^{th} DMU in time t . Whereas the equation (12) shows the technological change, technical change, mix efficiency change, and residual scale efficiency change of i^{th} DMU in time t and the s^{th} DMU in time h . The decomposition of the TFPI is said to be complete in the sense that there is no unexplained component left.

Besides, these DEA is criticized for not modelling the possibility of endogeneity. Especially when the inputs are allocated based on the output, in simple words, the educational institutions that perform well and produce better results as compared to its peers, higher education commission will, in response, increase²⁵ their share in resources as a result of increased resources the efficiency improves. Further, schools with better outcomes with also attract students with high socio-economic backgrounds. Additionally, due to high merit, these schools give admission to students with high grades and abilities. Thus, the outcome of such educational institutions is high firstly due to socioeconomic status and the school resources.

Further, their abilities and family support also motivate them to perform better. Moreover, schools with higher pass rates have teachers with more abilities, experience, and education. Thus, the good student's results in these schools are positively related to the highly qualified teaching staff. Therefore, in the educational economy, a two-way causal relationship between inputs and outputs cannot be ignored (Cordero et al., 2013).

²⁵ Negative causal relation can also occur when the resources are cut down due to the poor performance/outcome.

4.3.2 Tobit Model

In the 2nd step, these calculated efficiency scores are regressed over the set of control variables using the Tobit model. Tobit Model is a discrete model where some of the observations are missing out of certain range of variables in the regression model, this missingness with limit the range of variations in the dependent observed variable. The censored model is available when at least the independent variables are observable and available (Üçdoğruk et al., 2001). Therefore, Tobit model is used in the study which is as follows:

$$y_i^* = x_i^T \beta + u_i \quad (4.13)$$

Where y_i^* is the dependent variable, and x represents the vector of dependent variables, β is the vector of unknown parameters. The range of y_i^* is defined as follows:

$$y_i^* = \begin{cases} x_i^T \beta + u_i, & y_i^* > 0 \\ 0, & y_i^* < 0 \end{cases} \quad (4.14)$$

The Maximum Likelihood estimation is used to obtain the estimated parameter values, and the error term is assumed to be normally distributed, further is consistent and asymptotically normally distributed (Üçdoğruk et al., 2001). Kounetas et al (2011), Wolszczak-Derlacz and Parteka (2011), Lee (2011), Mancebón et al (2012), Johnes et al (2012), Burney et al (2013), Duh et al (2014) and others also used the similar approach. The robust approach of conditional estimators is also used for the non-parametric models (De Witte and Kortelainen, 2017).

4.4 Data Analysis and Results

This section provides a brief overview of the data in a summarized form. Firstly, the description of all the input, output, and controlled variables that are used in the study are analyzed. Further,

this section also provides an overview of the techniques that are used for filling the missing data; moreover, the data is processed, outliers are removed, and it is made ready for the analysis step.

4.4.1 Description of Variables²⁶

Fried, Lovell, and Schmidt (1993) define educational efficiency by comparing the optimal level of inputs to the observed input levels used in the school's productivity. Thus for measuring efficiency data for the input and out variables are collected by using a survey for students.

Demographic Variables: The survey designed for the student can be divided into five different sections. In the first section of the survey, the different questions related to demographics and individual student characteristics are asked. Demographic variables used in this study are age, gender, marital status, disabilities, ethnicity, and religion. Additionally, the position of the students' birth order is also observed, i.e., is he/she the first, middle, or last child. Further, family pressure on individual students is also considered. The literature shows mixed results for the impact of different demographics on the efficiency of student performance.

Annual Marks: Annual marks in the 9th board exam of all the students who are enrolled now in grade 10th are taken as an independent variable. These marks are the indicator of students' performance over the year; however, there could be some unforeseen events due to which a student could not perform well.

Student's Abilities: For this model, we are considering student's abilities heterogeneous across the school. Abilities of individual students can be measured using three different sets of variables, i.e., cognitive (native abilities, i.e., ability to memorize, think and reason), non-cognitive

²⁶ See Appendix section for detailed questionnaire

abilities (affective, i.e., social skills and classroom learning abilities) and psychomotor skills (out of school learning)²⁷. Abilities are expected to be positively related to efficiency level.

In the second section of the questioner student's abilities are measured. The cognitive abilities are measured through a different set of question-related to English, Urdu, Mathematics, and analytical skills. The main goal was to measure the ability of the student to read and understand the questions asked and provide the correct answer from the options given. So, the cognitive abilities are measured by the total marks obtained by a student, i.e., the student with the highest mark is the one showing higher cognitive ability.

Non-cognitive ability is measured using the Interpersonal Competence Questionnaire (ICQ)²⁸ through a different set of question-related to domains self-control, self-esteem, social expressivity, social sensitivity, emotional support, and conflict management. Thus, purpose was to develop a similar scale, which is representative of the Pakistani population. This instrument is a questionnaire designed to measure attitudinal and behavioral characteristics. A 5-point Likert scale is used to measure the strength of the agreement of the student with the set of the question asked to measure non-cognitive ability, where 1 is chosen when the respondent strongly disagrees with the question asked, and 5 is chosen when he strongly agrees. The quantification of the non-cognitive abilities index was constructed based on the average values of each dimension. The final variable of Student ability is constructed by giving equal weight to cognitive and non-cognitive ability.

²⁷ It was not possible to measure the psychomotor skill of the students, that is why it was not used in measuring the student ability.

²⁸ ICQ was developed by Buhromester and colleagues in 1988 to measure the social competence by multi-dimensional scale.

Effort level: The third section of the survey measured the number of hours spends on doing different activities. Data related to Time spend on getting formal Education in school (approximately 8 hours), time spent on doing Self-Study, time spent on getting Private Tuition or help, is measured. The respondent was allowed to reply in hours and minutes for each type of question asked. Student effort level score is constructed based on the average value of three components, i.e., the time spent in school, the time student spends on self-study, and time spends on private tuition.

Students Financial Resources: The fourth section consists of question-related to educational expenditures, to have a rough idea about the available financial resources for educational expenditures. The Students budget constraint is measured by observing the data on the monetary benefits he/she receives out of the total families' educational budget. As a proxy, the family expenditure on the individual student can be measured as a sum of school fee, additional tuition fee, expenditure on books, copies, and uniform and transport changers. Further, is the student receiving any grants or scholarship from school is also part of its financial resources. Expenditure is recorded in rupees. Financial resource index is calculated using the average values of expenditure on books/copies, uniform, transportation, tuition fee, pocket money, and amount of scholarship received.

Socioeconomic status of students Family: students having a strong family background receive more resources from their families. Thus, if a high proportion of students belong to disadvantage families, it will harm efficiency. Further, it can be seen in the case of Pakistan that the majority of the student in public schools belongs to the poor or middle class (Alexander and Jaforullah, 2004; Jeon and Shields, 2005; Rassouli-Currier, 2007; Alexander *et al.*, 2010). Family structure (joint or nuclear), family values (conservative/moderate), family income, family size

(number of school-going children amongst whom the families' educational expenditures will be divided), parental education, occupation, parent-children bonding/relationship, availability of the internet and parental visit school is measured to observe the family level resources and features.

School Location: This indicator is used to specify whether the particular school is located in an urban or rural area. A dummy variable is used for school location, and it takes the value of "1" if it is located in an urban area and a value of "0" if it is located in rural areas. The expected sign of the school location coefficient could be positive or negative. It was based' on the fact that urban schools have more and quality resources available as compared to rural schools. However, based on the high enrolment rate, the resources allocated to each pupil could be less than the resources received by a pupil studying in the rural school. Earlier literature suggests mixed results for the location effect of efficiency.

Student Output: measured as student achievement, the overall annual result of the respective board. The marks in individual subjects, i.e., English, mathematics, Urdu, and science subjects. The student's outcome is measured across different subjects to see if there is some difference in performance across subjects.

To measure the socio-economic status of the student's family, different questions related to family characteristics are asked. Some of the questions are open-ended while for other different categories are provided to record the response.

4.4.2 Sample Selection Criteria

The public schools in district Mardan are considered as the targeted population. This decision was taken based on the data for the learning score taken from Alif Aliaan. Learning score is defined as "a weighted average of the literacy rate of the population age 10 and above and percentage of class

5 students who can read in Urdu, English, and can perform a two-digit division. Equal weights are given to these 2 indicators.” Learning score for Mardan district was 50, which shows that there is potential to improve the performance. Further, it was interesting to see the data at more disaggregated level, which can explain the reason for low performance. For the analysis of student’s performance, the population of students from 10th grade are selected. There are 167 higher and 67 higher secondary schools across district Mardan, in which approximately total of 14289 students are enrolled in grade 10²⁹. Out of the total, 62.82 percent of students are enrolled in tehsil Mardan, 16.59 percent are enrolled in Katlang, and 20.59 percent are enrolled in Takhat Bhai. The enrollment of male students is almost double the females at the district level. The disaggregation at rural and urban level shows that in tehsil Mardan 68.68 percent are enrolled in rural areas (72 percent are male students and 28 percent are female students), and 31.31 percent are enrolled in the urban areas (70.4 percent are male students and 29.55 are female students). In case of Katlang 80 percent students are enrolled in rural areas (65.6 percent males and 34.3 percent females), and 20 percent are enrolled in urban areas schools (48 percent males and 52 percent females). In the 2nd largest tehsil of Mardan district is Takhat Bhai which is mainly a rural area, 92 percent of the students are enrolled in the rural area schools (49 percent male students and 51 percent female students), and 8 percent students are enrolled in the urban area schools (25 percent are male and 75 percent female students). It can be easily seen that in Katlang and Takhat Bhai tehsil the ratio of female enrolment is more than the male enrolment in urban areas³⁰.

Out of total 183 high and higher secondary schools in the district Mardan, 32 schools are selected randomly from three tehsils. Further, to ensure randomization school’s name is written on

²⁹ In this study we are only referring to the students of higher and higher secondary schools enrolled in grade 10.

³⁰ Statistics calculated by author based on the school level enrolment data provided by Academy of Educational Planning and Management, District Education Profile, (2015-16).

small white papers slips for each tehsil separately and the sample is chosen through the lottery. All the students present in grade 10 science section, at the time of the survey, are selected for the survey. The final sample size was reduced to 30 due to unavailability of grade 10 students at two of the selected schools.

Figure 4. 1: Sample Size distribution by Tehsil

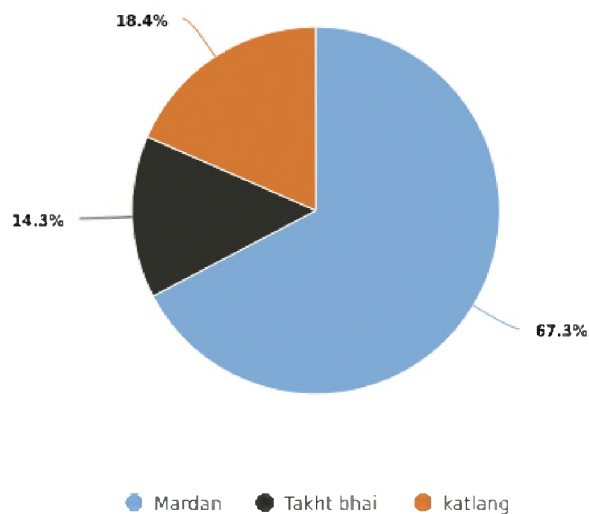


Table developed by Krejcie and Morgan (1970) is used by most of the researches to determine the size of the simple to be selected. However, due to the geographic and demographic segmentation of district Mardan, the sample size was reduced. Further, time and cost were another factor due to which the sample size of schools cannot be increased. An approximately equal number of rural and urban school are selected so that we can clearly see the difference in the student performance across the geographical location. Out of the total 30 schools, 16 schools belong to the rural areas and 14 school are from the urban area. After visiting the selected school,

I was able to collect the data for 625 students enrolled in rural areas and 705 students are from urban areas. Further, disaggregation is shown in the table 4.1 and 4.2 below.

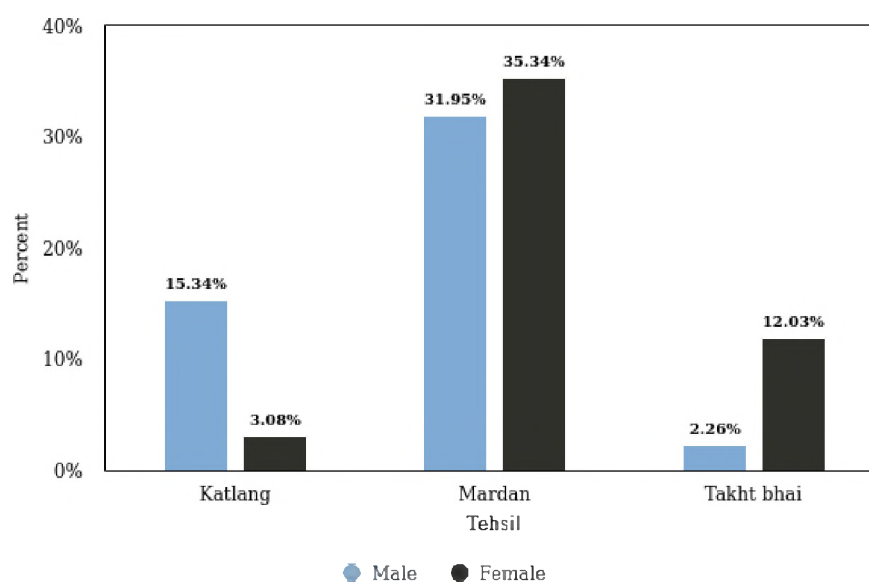
Table 4. 1: Number of Schools Selected by Gender and Tehsil

	School Sample		
	Male	Female	Total
Mardan	9	13	22
Katlang	1	3	4
Takhat Bhai	3	1	4
Total	13	17	30

Table 4. 2: Number of Enrolled Selected Student Disaggregated by Gender and Tehsil

	Student Sample		
	Male	Female	Total
Mardan	425	470	895
Katlang	30	160	190
Takhat Bhai	204	41	245
Total	659	671	1330

Figure 4. 2: Sample distribution by Gender



4.4.3 Detecting outliers and Cleaning of data

Outliers can cause serious issue when applying statistical techniques for analysis. The outlier mostly arises due to the measure error, thus the resulting analysis do not represent the underlying functioning of the system. Therefore, it is recommended to remove the outlier before apply any statistical analysis technique. Atkinson and Hawkins (1981) defined outlier as the observation that is different from the rest of the observation so as it feels like it was generated from a completely different mechanism. Alternately, outliers are the extreme value that deviates from the rest of the data set or overall pattern of the selected sample. The most common outliers in the data arise at the data entry stage, wrong choice of instrument, experiment or survey design, sampling error and the data processing error. Other types of outlier that do not arise due to error in the processing rather represent the true value is called the novelties.

There are many methods discussed in the literature to detect outlier in the data like a numeric outlier, DBSCAN, Z-score and isolation forests. Other methods include expectation maximization (EM) and Principle Component Analysis (Alkan *et al.*, 2015), however, we will only discusses the most commonly used method in this study. Outlier detection method also depends on the type of outlier i.e., if it's a univariate outlier then it can be detected by looking at the graphical representation of the data, more specifically the distribution of the variable. For a multivariate outlier it is hard to detect the outlier by simply analyzing the distribution of the data, therefore we need the help of statistical model to detect the outlier (Seheult *et al.*, 1989; Seo & Gary, 2006).

Most commonly used techniques are the numeric outlier, DBSCAN and Z-score method. The numeric outlier is a nonparametric method mostly used for the detection on univariate outlier. In this one-dimensional method outliers are identified using the interquartile range. Thus, the

outlier is a data point that is greater than Q_3 and less than Q_1 . Another commonly used nonparametric technique to detect outlier is the DBSCAN³¹. This technique is based on the data analytics-clustering algorithm, which focuses on the neighboring value. All data point are either core, boarder or noise points. Core points are the neighboring points that have the least *MinPts* within a specified distance. The boarder points are the neighbors of the core point but it has less *MinPts* neighbors, and all the other data points are the defined as the noise point also referred as the outliers. Further, Z-score method is also commonly used to detect the outlier in univariate method. It is a parametric method that uses Gaussian distribution and the outliers lie on the tail of the distribution far away from the mean value of the data. The value of outlier also depends on the threshold Z-source. The most commonly used threshold Z-score are the 2.5, 3.0 and 3.5, any observation greater than the specified threshold is identified as an outlier.

Tukey (1977) boxplot outlier method is used to detect outlier in this study for continuous data and for categorical data graphical analysis is used to detect the outliers. This method uses the graphical tool to exhibit the lower extreme, lower quartile (Q_1), median (Q_2), upper quartile (Q_3) and upper extreme values from the data set. Further, inner and outer fences are defined to detect the outlier in the data set. The inner fences are the point defined at a distance of 1.5 IQR, area below the Q_1 and above Q_3 . Further, the outer fences are the point located at a distance of 3 IQR, area below the Q_1 and above Q_3 . The value that lies between the outer and inner fences is the possible considered as the possible outlier, however the values that lie beyond the outer fences i.e., the extreme values are the probable outlier. Inter Quartile Range is calculated by taking the difference between Q_3 and upper Q_1 . Further, the outliers should be deleted from the data set as it affects the estimated parameters. The observations that lie outside the 3 IQR (Inter Quartile

³¹ Density Based Spatial Clustering of Applications with Noise

Range) are deleted from the data set and are considered missing, whereas the novelties will be used as it is for the analysis process. The deleted outlier is treated as the missing data and is filled with the imputation method.

4.4.3.1 Missing Data

Working on missing information is a challenge that is faced by many researchers working in the area of qualitative data. Data in case of education is seldom complete. More specifically in case of primary data collection related to educational research the issue is more severe (Cheema, 2014a). The presence of missing data in the variables has become a rule rather than an exception in survey that is conducted on a large scale (Sharpe, 2008; Dong & Peng, 2013). Analysis of the data that have significant amount of missing data can result in misleading conclusion and the finding from the study cannot be generalized for the policy implications. Further, the non-respondent may be completely different from the ones who responded completely, therefore delating case may cause biasness the results. Most of the data analysis software are designed to work with complete data set and analysis with missing data sets may provide misleading results. Further, delated cases can lead to loss of information that was collected for the targeted population. Given the importance of the missing data and the complications that can arise, it is significantly important for the researches to report the proportion of missing data. However, there are few guidelines available on how to diagnose the missing data patterns and remedy to hand the problems caused by missing data.

Most of the statistical test are designed for the complete data sets, failing to complete the data set can lead to error in the statistical process and violations of the basic assumptions of the statistical tests. Further, the proportion of missing data can also affect the attributes of the data and the results associated with it. Therefore, it is recommended that the

essential information related to data should be reported, particularly the percentage of missing data and the process that should be used to handle the missing information.

4.4.3.2 Missing Data in Primary Research

In primary data research, there can be many causes for the missing data. Some respondents who refuse to answer the questions that have privacy issue, like the questions related to the family income. Or the respondent did not understand the question that was asked. Another case is when the respondent wants to answer the question but it was not given in the options provided. Further, other possible reason could be the time limitation or the respondent have lost his interest in the questionnaire. Therefore, in most of the cases the reason for the missing data is either the research design, communication issue with the participants or because of the interaction between the two (IBM, 2009). Broadly speaking the reasoning for missing information can be divided into two groups. Firstly, the case when the respondent participates in the survey but do not provide information about each and every item, which is commonly referred to as the “item nonresponse” in the research.

Another most commonly discussed reason for missing data in literature is the participant attrition, in which the researcher has to record the participant’s response periodically. However, due to the unavailability of some of the participant we cannot record their response. Most common case of the attrition is in the household level survey or the survey related to education when the researcher have to collect the data of students everyone but he may have left the school due to some reason. Further, if the data is collected periodically and some of the participants are not available so the data for those participants is usually missing. In case of experimental/quasi experiment design studies, the experiment is being repeated many times in

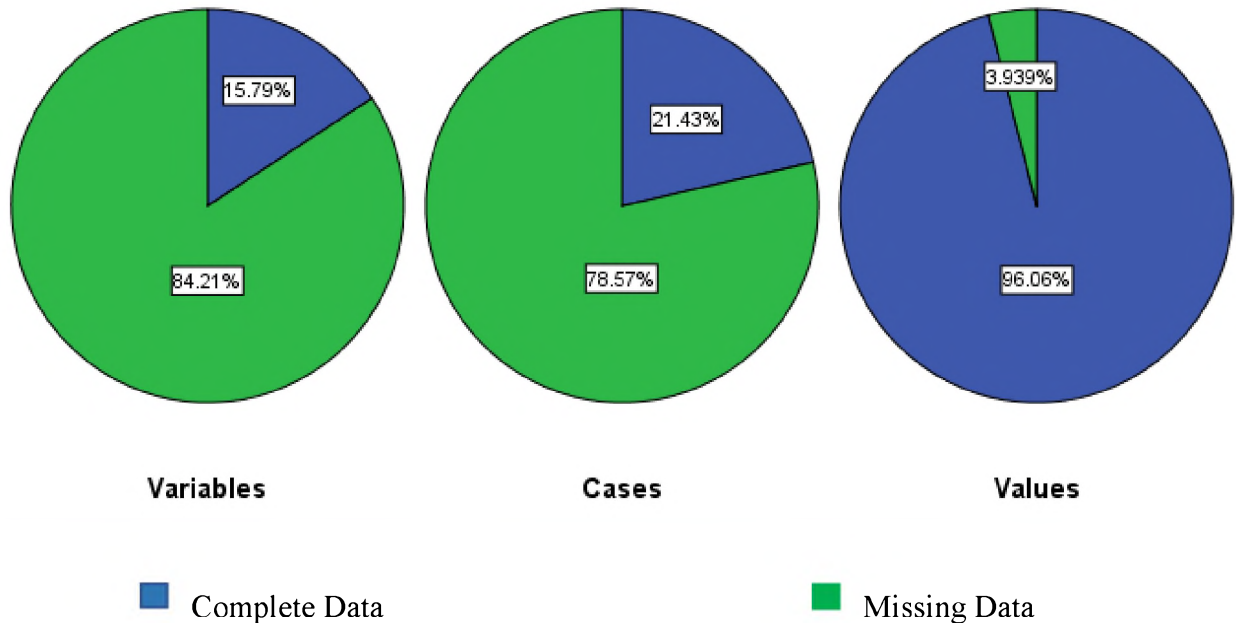
different phases, therefore some of the participants may drop during the process because of some work engagements (Schlomer *et al.*, 2010).

The same situations may also occur when collecting data through questionnaire across different sections. The participant may leave some field empty due to boredom or fatigue. Further due to privacy issue some of the section can be left empty (Schafer & Graham, 2002). Therefore, the problem of missing data can arise at the time of data analysis. In this situation the percentage of missing data as a whole and missing information for specific field should be reported separately (Mishra & Jain, 2016). The ideal approach to deal with the missing data is to design strategies that can help to avoid the item non-response.

Missing data in quantitative research is very common. Rousseau *et al.*, (2012) reported that the missing data of 15percent to 20percent is very common in research that is conducted in the educational sector. However, the researches in the quantities research have not reached to any consents regarding the percentage of missing that will create problem. Some of the researchers are of the view that a 5percent missing data is the cut-off point, where as some others are of the view that a missing data of more than 10percent can cause biasness in the statistical analysis, whereas some other researcher considers 20percent as the cut-off point (Bennett, 2001; Pigott, 2003; Dong & Peng, 2013; Newman, 2014; Little & Rubin, 2015).

Figure 4. 3: Overall Summary of Missing Values

This figure shows the percentage of missing data across cases and variables. It shows that the data of 15.79 percent variables is complete



The missing data analysis shows that overall, 3.93 percent of data is missing. Some researchers suggest to delete the missing data (Pigott, 2001; Bennett, 2001); however, it can be seen that 21.43 percent of cases are incomplete (Figure 4.3). Further, if we consider the missing data for each variable, it can be seen that 15.79 percent of variables are not complete. Therefore, if we only consider the complete case, then the sample data cannot represent the whole population, and the results will be biased. Table no. fill it --- shows the summary of variables with missing date more than 10percent. The reason for the missing information may be because the respondents could not understand the specific questions, or they don't know whom to respond to these questions. Detailed information on the missing variable percentage is shown in table 4.3.

Table 4. 3: Summary of variables with missing data more than 10 percent

	Missing		Valid N	Mean	Std. Deviation
	N	Percent			
Number of parent and teacher meeting at school in the last 12 months	222	16.7	1108	1.57	2.6
Time spent on any paid work.	202	15.2	1128	.67776	1.20
Monthly Transport expenditure	178	13.4	1152	617.80	756.13
Disability	164	12.3	1166		
Time spend on other activates.	149	11.2	1181	2.01988	1.86

4.4.3.3 Missing data Mechanism

Many researchers are of the view that the pattern of missing data needs to be considered along with the amount and the source of missing data (Baraldi & Enders, 2010; Graham, 2012; Mazza, Enders, & Ruehlman, 2015; Joseph L. Schafer & Olsen, 1998; Josepn L. Schafer & Graham, 2002). There are some variables in which data is missing randomly, i.e., they do not show any fit pattern when the data is missing. Whereas there could be other variables that clearly shows that there is a visible pattern in the missing data, like the section related to income and expenditure, may be missing. Thus, the sensitivity of the questions also and how it is being asked can so be a cause for the missing data. In this situation, the missing data is non-random, and potential biases can be predicted in advance for such variables. There are number methods available in the literature to

analyze the variable with the type of missing data. Neither the less, the consequence is that it is beyond a researcher control to avoid the missing data. Regardless of the reason for the missing data, it affects the validity and the reliability of the statistical influences that cannot be ignored. Crucially speaking, it doesn't mean that the information available in the variables with missing data is not important for the researcher; however, we need methods to recover the missing information and incorporate it in the statistical modelling.

The modern methods of analyzing the missing data process are based on the work done by Little and Rubin (1987). The work done by the authors classified the missing data into three “mechanism” based on the patterns and statistical properties in which the data is missing. The three divisions are as follows; *Missing Completely At Random* (MCAR), the second mechanism is *Missing At Random* (MAR), and the third mechanism is *Missing Not At Random* (MNAR). As the properties of the missing data can vary from the original data, therefore it is important to use different methods to analyze the missing data. Thus, by using different methods to analyze the missing data can give us information about the best methods that can be utilized under given conditions.

Missing completely at Random (MCAR) is refers to as the situation when the missing data do not show any pattern, and the missing values are not related to any of the items and variables that are being studied. Further, the missing value is also not related to the variable itself. For example, if any of the dependent value is missing in the data set, and it is also unrelated to any of the explanatory variable. Further, a missing dependent value is also not related to itself. MCAR also refers to the situation when the missing data is randomly distributed across the data sets. Rubin (1976) is of the view that the situation in which when the missing data can be deleted completely and the reduced sample size is still representative of the target population, then such type of

missing data can be referred to as the MCAR. However, if the reduced sample is not representative of the target population, then the results from the data analysis process cannot be generalized for the whole population.

Further, the data set with missing data can be considered as the subset of the whole sample, and the difference between with and without missing data can be used for the partial check. Considering all the mechanisms of the missing data, MCAR is the easiest one to handle as it only reduces the sample size (reducing the power of the test), but the analysis from the reduced sample is considered free of any biasness (Josepn L. Schafer & Graham, 2002). Another condition attached to MCAR is that the missing data ratio should not be more than 5percent ³². In case when the missing data is more than the specified threshold level, then deleting the missing data from the data set is not desirable. Thus, to get the unbiased and consistent estimates of the parameters, it is recommended that the missing data should be imputed (Cheema, 2014).

When the missing data set, do not fall under the category of MCAR, then it could either be the case of MAR or NMAR. The second mechanism of the missing data is *Missing at Random (MAR)*, where the missing data is not related to the variable itself; however, it can be related to other items or variables. For example, a missing value in the dependent variable can be related to explanatory variables, but it is not related to the dependent variable itself. Allison (2001) is also defined MAR as the probability of relation of missing data with other variables and not related to the variable of interest, i.e., the dependent variable. Thus, we can say that in the case of MAR mechanism, we can say that the values are not missing at random. Alternatively, MAR is the missingness in the data that is related to the observed data set, i.e., explanatory variables and not

³² Different percentage have been considered by different other, as discussed in the first half of this section.

related to the missing data itself (Graham, Cumsille, & Elek-Fisk, 2012). Missing data due to questionnaire design can also be the case of MAR, where the response of one question is dependent on the response of other questions, like if the answer to the first question is yes, then you have to skip the next question. In this situation, the missingness is one variable that is dependent on the other variable. In the case of MAR mechanism, the missing data can be predicted based on the observed data; however, the missing data should be less than the suggested threshold level.

Not Missing At Random (NMAR)³³ is the case when the participant does not provide information about any specific items. NMAR is also referred to as the non-ignorable missingness. Allison (2001) describes NMAR as the probability that the missing data is the function of itself. This situation usually arises when you ask for the participant's income in a survey questionnaire. The chances that the individual with a high income will not answer this question is very high. In this case, the missing information on salary cannot be filled based on the available information on the salary of other participants. Thus, in this mechanism, the missingness depends more on the unobserved data, thus because for the weak correlation of the missing date with the observed data, it is very hard to impute the missing data accurately. Therefore, discourage the effectiveness of the use of the usual imputation methods. In this situation, researchers suggest modelling the missing data mechanism as part of the estimation process. Whereas, in the case of MCAR and MAR, we don't need to model the missing data as the issue can be handled effectively through other imputation methods. However, researches have not reached any clear acceptable method that can be used to deal with the missing caused by the mechanism of NMAR.

³³ Also referred as Missing Not at Random (MNAR)

The real survey data is not always aligned with the three mechanisms that are discussed by Little & Rubin (1987). However, the real survey data is a combination of different categories of questions like dichotomous questions, multiple-choice, rank order scaling, rating scale, semantic differential scaling, staple scale, demographic and open-ended questions. Schafer & Graham (2002) suggested that the methods that are used to deal with the issue of MAR can also help to cope with the issue that may arise due to MNAR. In case when the MNAR is incorrectly identified as the MCAR or MAR, then the missing data is not being modelled correctly and thus the parameters estimated will be biased. Similarly, if the MAR or MCAR are incorrectly identified as the MNAR then it indicates that a more complex method is being used in handling missing data issue. Therefore, identifying the type of missing data mechanism is crucial in data handling process. However, it is not always possible to statistically identify the type of miss data mechanism, as only few statistical tests are available.

4.4.3.4 Diagnosing the Mechanism of Missingness

There are only a few methods available in the literature to detect the mechanism of missingness in the data. However, we cannot get a straight forward answer to the mechanism of missing, but it is useful in identifying the appropriate analysis. Therefore, different methods can be used to detect and decide the reasonable assumption for the missing mechanism. In most of the case, it is not easy to differentiate between the MAR and MNAR cases based on the type of questions. More sensitive to the questions are, it's more likely that the respondent will not provide information about it; this is clearly the case of MNAR.

Further, the assessment of MNAR depends on observed covariance and the unobserved components, whereas MAR only depends on the observed outcomes and the covariance. Zhou *et*

al. (1999) suggested a model based on the likelihood ratio, with null that the data is MAR with an alternate that the missing pattern is MNAR. However, the correct specification of the ratio test is significantly important. Such tests do not provide any strong evidence against the presence of MAR hypothesis as the MNAR model has a MAR model with equivalent fit to observed data (Molenberghs *et al.*, 2008).

A simple way to detect the MCAR in the data is to compare the means of data with and without missing data using the pair-wise t-statistics. However, these methods can result in different complications at the time of comparison. To distinguish between MAR and MCAR, Little (1988) developed a test based on the assessments of the means of the observed data using chi-square statistics. In the case of MCAR, the calculated means will remain the same at each assessment, whereas if the data is not MCAR, then the means values vary for each assessment across the pattern.

Other tests that are used in literature are LS test proposed by Listing and Schlittgen, (1998) to determine if the dropouts are at random. Ridout's logistic regression method is used to check if the dropouts within each treatment group are random or they are related to the specific covariate. Fairclough (2002) proposed to test the missingness in data set by using the logistic regression. The difference between the MAR and MCAR can be tested by examining the association between missing data and the observed dependent variable. After the adjustment of association, the covariance is forced into the model. If the observed score has a significant role in predicting the missingness, then this is evident that the data is MAR.

Waersted et al. (2018) discuss that the pattern of missingness can be monotone, intermittent, and mixed³⁴. However, Little Test is the only test available that can handle all types of missing patterns. In this study, we have missing value in the observed data, i.e., intermittent. Therefore, we used the Little's Test for detecting the mechanism of missingness in our dataset. There are many extensions for the Little's test based on the type of data and the estimation technique. An extension of Little's test for missing longitudinal data was proposed by Park and Davis (1993), in which Wald test statistics were used. The proposed method improved the results for data set that applied weighted least squares estimation. To forgo the distributional assumptions, Chen and Little (1999) extended the little's test to generalized estimation equations. Another extension is proposed by Kim and Bentler (2002) for the structural equation models. In this test, the homogeneity of means and covariance (HMC) are assessed, if the data set with missing values reject the hypothesis for HMC, then it implies that the data set is not MCAR. Jamshidian and Schott (2007) also followed the same technique introduced by Kim and Bentler (2002); however, they also allowed for the partitions in cases that have more than one missing pattern.

Little's Test

Let y_i be the observed data set with p -dimensions. It is assumed that the data is multivariate normally distributed with means μ and covariance Σ , with missing y_i s. Little's test (1988) still works even the data is distributed asymptotically; however, in this situation, this test is not suitable for the categorical variable. We suppose that for J number of missing patterns, there are o_j observed components and m_j is the missing components. Further, $p_j = |o_j|$ is the j^{th} pattern of the observed

³⁴ *Monotone*: the respondent drops permanently out of the study, often referred to as attrition or dropout.
Intermittent: missing observations between the observed.
Mixed: an intermittent pattern followed by monotone missingness.

component. The observed mean vector and the covariance matrix of the j^{th} pattern is represented by μ_{oj} and Σ_{oj} . Assume that \bar{y}_{oj} is the sample mean of the observed component of the j^{th} pattern. The index of pattern j is represented by I_j and its value range from 1,2, ..., n and $\sum_{j=1}^J n_j = n$. Lastly, we assume that $n_j = |I_j|$.

Based on these assumptions we can define the χ^2 statistics of Little's test for MCAR as

$$d_0^2 = \sum_{j=1}^J n_j (\bar{y}_{oj} - \mu_{oj})^T \Sigma_{oj}^{-1} (\bar{y}_{oj} - \mu_{oj}) \quad (4.15)$$

Now assume that r_i is the conditional missing indicator, the data is MCAR if the following null hypothesis holds

$$H_0 : y_{o,i}|r_i \sim N(\mu_{oj}, \Sigma_{oj}) \quad \text{If } i \in I_j, 1 \leq j \leq J \quad (4.16)$$

If the null hypothesis does not hold, then it shows that the means value of the observed data is not the same across all patterns.

$$H_1 : y_{o,i}|r_i \sim N(\nu_{oj}, \Sigma_{oj}) \quad \text{if } i \in I_j, 1 \leq j \leq J \quad (4.16)$$

The mean vector ν_{oj} can be different for each j pattern, where $j = 1, 2, \dots, J$. The acceptance of alternate hypothesis is the sufficient condition for the rejection of MCAR and not the necessary one. In case when the assumption of normality holds then the Little's test follows the Chi-square distribution with $df = \sum_{j=1}^J p_j - p$. On the other hand, if the multivariate normality assumption does the hold, but the vector means and the covariance matrix are the same, then the Little's test will follow the same chi-square distribution asymptotically. Normally the estimates of mean and the covariance are not known Little (1988) suggested that unbiased estimates can be calculated by using the EM algorithm, given the MCAR null hypothesis. Asymptotically, if d^2 follows a chi-

square distribution with $df = \sum_{j=1}^J p_j - p$, then the null hypothesis of MCAR will be rejected if $d^2 > \chi_{df}^2(1-\alpha)$, concluding that data is not MCAR for the given level of significance α (Little & Rubin, 1987; Schafer & Olsen, 1998).

For Missing Value Analysis (MVA), Little's test is performed on SPSS using the EM algorithm, and the results show a chi-square value of 66193.348 with a degree of freedom 64433 at 5percent significance level and conclude that the data are not missing completely at random. According to Little's (1988), if the data is not MCAR, then it could be MAR; therefore, it is necessary to check the possibility that the missing values may depend on the values of another variable. Schafer and Graham (2002) state that it is not possible to test if the data is MAR; however, different statistical tests can be used to check the missing mechanism. For this purpose, a separate variance t-test is performed, and a value signification p-value at 5percent is an indication that some of the values are correlated with the other variable, there indicates that the data is MAR.

4.4.3.5 Handling the Missing Data in Survey

Many methods are discussed in different filed of literature that is used to fill the missing data (Little, 1988; Rubin, 1976; Allison, 2003; Laird, 1988; Schafer & Graham, 2002; Richards, Little, & Rubin, 2006; Kossinets, 2006; Clarke & Hardy, 2009; Schlomer et al., 2010; Little & Rubin, 2015). Most of the literature assumes that the data is continuous when they are discussing the issue of missingness; however, few studies are available that discuss the missingness in the categorical variable (Gao, 1999; Allison, 2001; Chen & Åstebro, 2003; Sentas & Angelis, 2006; Graham, 2009; Li, 2009; White, Daniel, & Royston, 2010; Kropko *et al.*, 2014; Nishanth & Ravi, 2016). There is a general agreement among academic researchers that technique that will be considered best for evaluating the missing data is the one that will minimize the biasness, maximum

information can be used, and that will reduce uncertainty in the estimates yield, based on the fact that the standard errors are minimized and are significant. The cited literature shows that conventional methods do not perform well based on these criteria. Whereas, methods based on the multiple imputation and maximum likelihood are emphasized and recommended based on the fact that they perform very well based on the criteria mentioned above. The most commonly used methods to deal with the missing data discussed in literature can be divided into two main categories. The methods that rely on discarding the portion of the sample with missing data are part of the first category, like listwise deletion and pairwise deletion. At the same time, the methods that focus on filling the missing with computed data is part of the second category, including statistical data imputation, imputation based on machine learning, model-based imputations with maximum likelihood estimates with EM algorithm and other machine learning techniques including ensemble method, fuzzy logic, decision tree, and inductive algorithm and supportive vector methods.

These data imputation techniques can also be divided into non-stochastic single imputation methods (mean substitution, regression substitution, hot deck, k-nn, and others) and stochastic imputation methods (expectation-maximization, multiple imputation, recurrent neural network imputation, and others). The classification of missing data techniques can be seen in figure 4.2.

The conventional deletion method is not a technique to solve the missing data issue; rather, this is an approach used to ignore the missing data. Most of the studies suggested that this method is recommended when the missing data is too small (e.g., 5 percent or less), and it can be ignored. Whereas in the case of large missing data, this technique is not recommended. The commonly used deletion method is the *listwise deletion*, where all the cases with missing observations are deleted from the sample. Pigott (2001) referred this method as the *complete case*

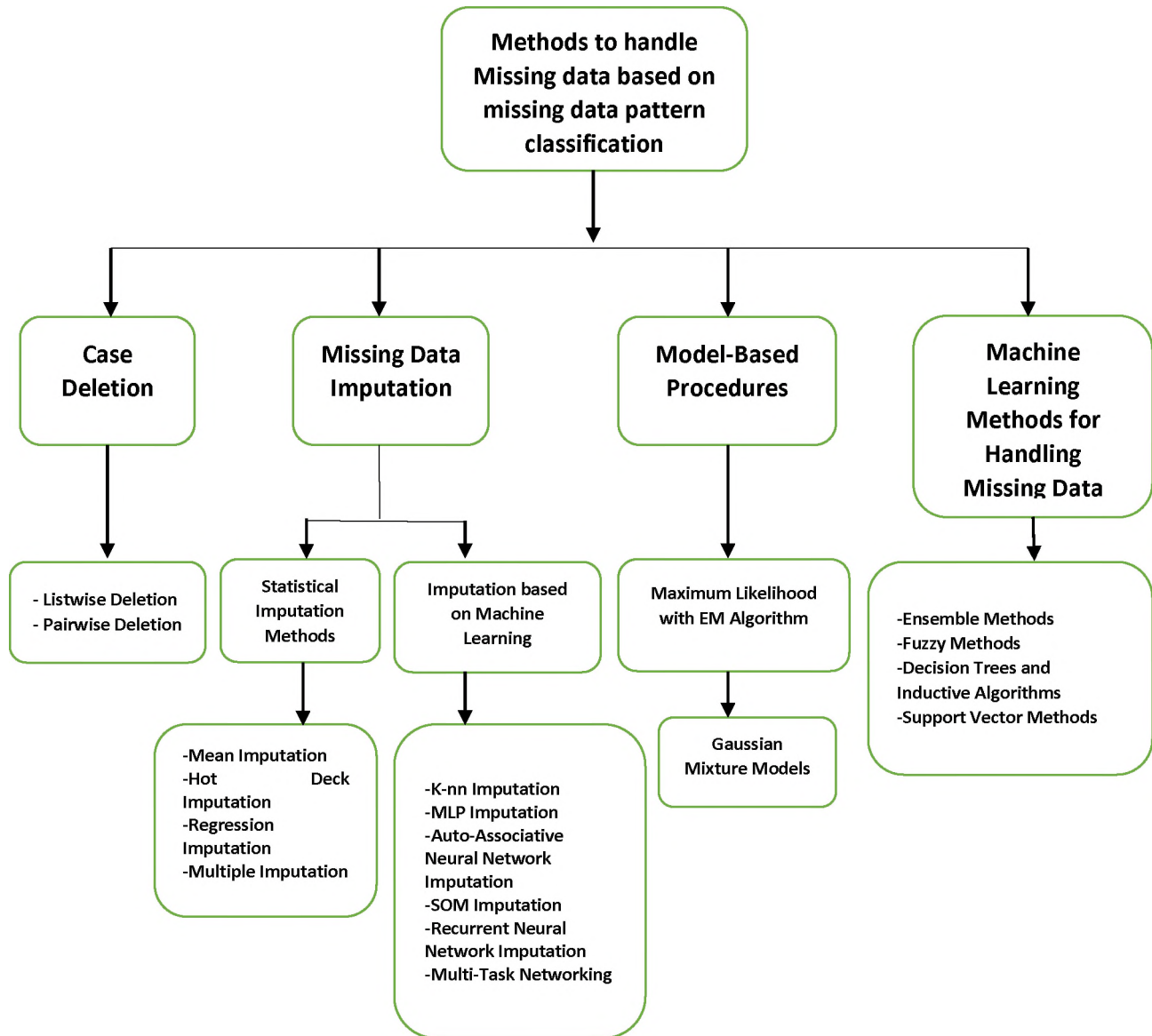
analysis because only those cases are included in the analysis that is complete. However, if there is a difference in the estimated results of the data with and with missing values, then the completed subsample is not representative of the full sample³⁵. Thus, this will cause biasness in the estimated results (Bennett, 2001).

Further, this method will drop all the cases with missing data, even if only one item is missing in the case. Therefore, it will cause a considerable loss in the statistical power and information because of partially missing data. *Pairwise deletion* is another method that is used to delete the missing cases from the data set; however, the only those cases are deleted from variables that are considered for analysis. Pigott (2001) referred to this method as the *available case analysis*, and the maximum information is retained from the data set. This method is used when we have to calculate the correlations and variance estimates, and a different subset of cases is used in calculating different correlations, i.e., the cases with missing data will be deleted, and the estimations will be based on the available information. The estimated parameters may show biasness if we are using the pairwise deletion method; however (Graham 2009) observed that for empirical data, the biasness tends to be small. This deletion method has limited application in the area of educational studies, as it involves more than two variables in the analysis, and we have to estimate two-way ANOVA tables and multiple regressions. Many data analysis software does not support the pairwise deletion. Further, the estimated results in the case of pairwise deletion and listwise deletion result in the same estimates (Graham, 2009). When faced with the missing data issue, the discussed complete case analysis is the commonly used techniques, but these techniques are not recommended (García-Laencina et al., 2010).

³⁵ The analysis is not the same with the data is MCAR (Cheema, 2014)

Figure 4. 4: Methods to Handle Missing Data

The figures show different methods that can be used to handle the missing data based on the patterns of missing data (García-Laencina et al., 2010).



Missing data imputation based on the statistical data is also very common. In this method, the imputed value is calculated based on the attributes of the patterns of the missingness in the data. Using this technique, we can impute a single value for each missing item, i.e., single imputation and, in some techniques, also allow to impute more than one value, i.e., multiple imputations (Figure 4.4). One of the most popular imputation methods is the *Mean Imputation*, in

which the missing value is imputed as the average of all the observed value of that component. However, the disadvantage of this method is that it ignores the variation in the data by under-representing it.

Further, this method also ignores the correlation between different components while imputing the missing data. Another commonly used single imputation approach is the *Hot and Cold Deck Imputation*; the idea behind this imputation technique is that the missing data is filled based on the information available from similar cases. The similarity in the cases may be based on the characteristics, ethnicity, and ideology of the individual respondent. In the case of Hot Deck, the missing data are imputed based on similar cases within the data set, whereas, in the case of *Cold Deck*, the data source can be different. The main disadvantage of this technique is that the missing value is imputed based on a single complete case, whereas there can be other cases with similar characteristics in the data set, which are not considered during imputation (Figure 4.4).

Further, hot and cold deck imputation also ignores the fact that the missing data can be correlated with the available data set. In this situation, the missing value imputation through regression analysis is recommended. In this process, the regression model is trained on the bases of available data and predicts the missing values. Further, the regression model (linear or nonlinear) to be selected depends on the type of data. In case the dependent variable is categorical, then we will use the logic or probit, regression model³⁶. In the case of more than one variable, multivariate regression may be applied at the data imputation stage. The advantage of this technique is that the missing data is correlated with the complete sample and is representative of the sample. However,

³⁶ In case of ordered categories, we will use the ordered logic and ordered probit model.

the disadvantage is that a single regression curve is fitted to the data set, which ignores the inherited variations.

Another technique that using the maximum likelihood approach and is commonly used in completing the missing data is the *Expectation-Maximization* (EM). Maximum likelihood approaches use the available data to estimate the statistical parameters, which are then used to complete the missing data set (Dempster, Laird, & Rubin, 1977). The EM is a two-step process; firstly, the missing data are filled using the regression imputation in which imputation is based on the initial observed values. In the maximization step, new parameters are calculated using the complete data in the first step. This process continues until the change in the estimated parameter is very small from one iteration to another, until the convergence is achieved by estimates (Allison, 2003). The EM method is preferred over the other single imputed techniques as it provides efficient and unbiased estimates of the parameters. However, it does not provide the estimates for standard errors and the confidence interval, for which an additional step is required.

The techniques discussed so far for imputation based on the statistical data only provide a single imputed value and do not discuss the uncertainty that is attached with the accuracy of predicting the missing value (García-Laencina et al., 2010). *Multiple Imputation* (MI) technique represents the uncertainty of replacing the missing value with a set of possible right values that can be imputed (Rubin, 1987). MI technique assumes that the data should follow at least MAR mechanism. The missing values are imputed M times to produce M different complete sets, thus capture the variation in the data. Each of the data sets completed are analyzed separately using the standard procedure, and the parameters are estimated. Average of M parameters are estimated across all the samples selected to get a single estimate. Thus, the results of the M completed set are combined for further analysis. Little and Rubin (1987) are of the view that regression

imputation performs better than mean, case wise imputation, and expectation-maximization; however, multiple imputations perform better than the others.

Maximum likelihood imputation (EM) and the multiple imputations assume that the data should be at least missing at random, opposite to the situation when the data is missing not at random (MNAR) and cannot be ignored. Another commonly used method is the *Full Information Maximum Likelihood* (FIML) that assumes that the data should be MAR and multivariate normality should hold in data. FIML uses all the available information in the dataset to estimate the standard errors, parameter value, and handle missing data in one step. Like MI, it does not impute the missing value; however, it treats the missing values in the estimation process. It follows an iterative process to find the set of parameters for which the overall likelihood function is maximized. There are many machine learning techniques available to handle missing data, but the focus of this study is on statistical analysis. Therefore, we are not discussing the machine learning techniques in detail. Overview of machine learning technique is available in García-Laencina et al., (2010).

In this study, we are using multiple imputation techniques to handle the missing data issue as it does not rely on the multivariate normality condition. SPSS specifies two methods based on the pattern of missing data, i.e., Full Conditional Specification (follows the Markov Monte Carlo algorithm) and Monotone method. SPSS can automatically select the imputation method based on the missing value pattern. The fully conditional specification is used when the missing value pattern is arbitrary, or the values are missing between the observed data. The monotone method is used when the respondent drops permanently out of the study, often referred to as attrition or drop out. Data is imputed using linear regression in case of scale variables, and logistic regression is used for the categorical variables. Conventionally, it is recommended that 3 to 5 imputed data sets

should be used to get the unbiased results; however, Enders (2011) is of the view that a minimum of 20 imputed datasets should be used as to get the optimal level of statistical parameters.

Further, the number of the imputed dataset should be increased if the proportion of missing data is greater than 50 percent. Suggesting that the number of imputations is directly related to statistical power. As the total missing data in this study is approximately 4 percent, therefore we are using 5 imputations. Further univariate descriptive analysis is performed after the imputation of the missing data, and it was observed that there is no significant difference between the mean and standard deviation of the original and the imputed data.

4.4.4 Infographics and Descriptive Statistics

This section discusses, in brief, the descriptive statistics and infographics of the selected sample to have a clearer understanding of the data. As discussed in the literature, the individual student characteristics, family characteristics, and school location influence the performance of students. Thus, this section discusses in detail all these sections as below.

4.4.4.1 Dependent and Independent Variables

In this section, summary/descriptive statistics is discussed for the dependent and independent variables that are used for the analysis. The statistics that are being presented are dis-aggregated across tehsil and available with gender segregation. Annual marks are the dependent variable that is used in this research. It can be seen that the average mean score for female students (366, SD=44) is higher than the male students (351, SD =61). It can also be seen that the Takht Bhai tehsil performed better amongst the three tehsils. For the test scores, females again performed better than the male students with an average value of 13.4, SD= 2.49, and 12.53, SD=3.02. A test score is

used as a proxy to measure cognitive ability, and tehsil Mardan performed, on average, better than the other two tehsils (Table 4.4).

The mean score of six dimensions is used to measure non-cognitive life skills or self-evaluating interpersonal competence. In the case of a male student, it can be seen that Takht Bhai has the highest average score in all the six categories; additionally, the score is even higher than the mean score attained by a female student in the majority of the categories (Chiesi & Primi, 2015). In the case of female students in Takht Bhai, they have more self-control, can provide emotional support, and are better in conflict management. Female students in Katlang reported a high on the average score for self-control (N), social expressivity, and social sensitivity. However, it can be seen that beyond the gender comparison, interpersonal competence is lacking throughout the selected sample. Self-control (N) represents the negative perception and is higher in the male student as compared to female students. Initially, self-control was considered as a signal domain; however, it was observed that the instrument developed was bi-dimensional, further it was observed the set of questions, showing positive self-perception and negative self-perception can be separated analyzed. Thus, there is a need to improve the self-confidence by improving all the six categories, which may result in improving the efficiency in students (Chiesi & Primi, 2015; Fazel & Aghamolaei, 2011; Harb, Abu Bakar, & Krish, 2014).

The average time score represents the effort level. The highest effort level score for a male is 4.29 (Takht Bhai), and for a female is 5.17 (Takht Bhai), representing that the female student spends more time and effort in studying. Further, the difference may also be explained by the cultural difference and the preferences of the parents; thus, the male student has to spend more time out of household responsibilities whereas girls are supposed to help their mothers within the household. Log of the average educational expenditure score is taken as a proxy for financial

resources; the highest average score was recorded for the female student of Takht Bhai with a standard deviation of 0.71. Whereas for the male student's average score of 8.14 with a standard deviation of 0.7 is recorded (Table 4.4).

This study used the Exploratory Factor Analysis (EFA) to investigate the structure of the factors to be included in each dimension of non-cognitive ability, effort level, and financial resources. The advantage of EFA is that it allows for analyses of the performance of each item in the construction of the variable. The maximum likelihood extraction method was used with the direct Oblimin rotation. SPSS provides five different methods of rotation, which are grouped into orthogonal and oblique rotations. Direct Oblimin and the Promax are part of oblique rotations. Tabachnick and Fidell (2014) are of the view that we should look at the correlations to decide between the choice of orthogonal and oblique. If the value of the correlation is lower than 0.32 (threshold defined by Tabachnick & Fidell, 2014), we will go for the direct Oblimin with is an oblique rotation method. However, Harper, Kim, & Mueller (1980) is of the view that low correlation does not make a considerable difference in the exploratory stage.

Further, the KMO³⁷ test is used to analyze if it is feasible to perform the factor analysis or not. The value of KMO lies between 0 and 1. The consistency of the instruments is checked by using the coefficient of Cronbach's alpha was used. The value of the scale is low for some dimensions and ranges from 0.3 to 0.69. A lower value of alpha can be explained by the low number of items selected in each dimension and is acceptable (Dall'Oglio et al., 2010). Nguyen et al. (2020) also supported the view and added in psychological research its common to have a low Cronbach alpha as these studies tend to measure the individual perspective.

³⁷ Kaiser-Meyer-Olkin

Based on the analysis of the responses by the students, it can be observed that for all the questions whose statement was short in 5 to 6 words, the factor loading was high, whereas, for other questions, it can be observed that the students had the issue in understanding the question. Another factor could be the language barrier; all, the question was translated into Urdu; however, the first language of the selected sample is Pushto. The official language in all the schools is Urdu that needs to be followed, and Urdu is also taught as the compulsory subject. Therefore, for policy-making, it is a clear indication that students who do not understand the long Urdu sentence, need to focus more on the subject, or they should be taught in the local language.

Table 4. 4: Summary Statistics

This table shows the summary statistics of input variables, ability, effort, and financial resources across three tehsils.

			Cognitive Abilities	Non-Cognitive Abilities (Life Skills)									
			Annual Marks	Test-Score	Self-Control (P)	Self-Control (N)	Social-Expressivity	Social-Sensitivity	Emotional Support	Conflict-Management	Effort Level	Financial Resources	
Female	Mardan	Mean	356	13.4	2.14	2.84	2.20	2.37	1.64	2.25	4.91	7.83	
		Std Deviation	55	2.49	.67	.75	.77	.87	.61	.83	2.13	.70	
		Minimum	195	0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	.50	5.12
		Maximum	489	19	4.17	5.00	4.75	5.00	5.00	5.00	5.00	12.08	9.53
	Takht Bhai	Mean	366	12.84	2.36	2.89	2.41	2.36	1.76	2.41	5.17	7.79	
		Std Deviation	44	2.56	.75	.78	.74	.92	.91	.87	2.36	.59	
		Minimum	253	6	1.17	1.38	1.00	1.00	1.00	1.00	1.00	1.00	6.49
		Maximum	473	18	4.67	5.00	4.25	5.00	5.00	4.67	11.67	9.01	
	Katlang	Mean	357	13.17	2.24	2.93	2.69	2.74	1.45	2.25	4.37	7.98	
		Std Deviation	63	2.14	.51	.69	.84	.94	.51	.81	1.43	.71	
		Minimum	182	7	1.50	1.25	1.00	1.25	1.00	1.00	2.33	6.05	
		Maximum	458	17	3.33	4.00	4.75	4.50	3.33	4.67	8.67	9.20	
Male	Mardan	Mean	326	12.53	2.21	2.89	2.24	2.35	1.80	2.24	4.08	8.03	
		Std Deviation	62	3.02	.72	.69	.75	.78	.80	.76	2.08	.87	
		Minimum	158	2	1.00	1.00	1.00	1.00	1.00	1.00	.00	4.61	
		Maximum	495	18	4.83	4.88	4.50	5.00	5.00	5.00	11.67	9.49	
	Takht Bhai	Mean	351	12.5	1.86	3.75	2.23	2.93	2.12	2.66	4.29	7.95	
		Std Deviation	61	3.44	.81	.59	.78	.82	1.10	.99	1.63	.74	
		Minimum	252	6	1.00	2.13	1.00	2.00	1.00	1.00	1.00	6.12	
		Maximum	497	18	4.33	4.50	4.50	4.75	4.67	4.67	8.65	8.98	
	Katlang	Mean	311	11.17	2.13	2.81	2.35	2.30	1.80	2.27	3.68	8.14	
		Std Deviation	74	3.25	.74	.74	.90	.82	.85	.81	1.86	.70	
		Minimum	150	2	1.00	1.00	1.00	1.00	1.00	1.00	.43	4.76	
		Maximum	491	17	5.00	5.00	5.00	4.50	5.00	5.00	10.00	9.37	

4.4.4.2 Individual Student Characteristics

This study considers both male and female students in the sample, “0 represents the gender of the male student” and “1” represents the female student. Student across the selected sample of schools shows that the average age of the majority of the student is 15 years and six months, with a minimum value of 12 years and a maximum value of 19 years. The average age observed for the three tehsils is the same with a difference of a few months.

Data on the student’s marital status is also measured. Male and Wodon (2016) reported that the results of the survey of women age between 18 to 22 years, according to which 18.7 percent was married as a child in Pakistan. Out of the total sample, the ratio of child marriage is highest in the Khyber Pakhtunkhwa, followed by Balochistan. Further, if we see the statistics across education level, it was reported that the trend is more common in females with no education and three percent of females at the level of high and higher secondary are married (Male & Wodon, 2016, p. 4). A similar result can be observed for the district Mardan as well, where only three married cases were reported out of the total sample. It also confirms the fact that the majority of married female students are not allowed to study. Therefore, education plays an important role in delaying childhood marriages.

Out of the total studied sample, 99.8 percent follows the religion Islam, and Christianity is observed as the minority in the region. When the question was asked about ethnicity to observe the data for the region of origin, the majority of 97.7 percent are Pushto speaking, and 2.18 percent belong to other ethnic groups, including Urdu speaking, Punjabi, Sindhi, Baluchi and others. A question against the number of siblings was also asked, and on average, there are six siblings, with a minimum of no sibling at all, and with a maximum of 15 siblings.

Many researchers are of the view that students with any type of disability struggle through the academic year (Tarallo, 2012; Brodke et al., 2014; S. Dong & Lucas, 2016; Galante et al., 2016). Similarly, students with disabilities are also reluctant to seek help for the difficulties that face during studies. The amount the sample, 8.94 percent (55 females and 64 males) of the students replied “Yes” to the question regarding disability. Out of the total students who responded yes, 1.43 percent belong to Katlang, 5.86 percent belong to Mardan, and 1.65 percent belong to Takht Bhai tehsil (Figure 4.5 in Appx.).

Participants of the survey reported different types of disabilities, amongst which more than 57.28 percent reported the issues related to eyes, either its weak eyesight or some eye-related allergies. Understanding problem (16.50percent) is the second most reported problem that students face, which is also referred to as the learning disability in the education literature (Shalev et al., 2001; McDermott, 2010; Volden, 2013; McDowell, 2018). Around 7.7 percent of the students reported the issue of memorizing the lecture. Approximately 6.80 percent of the students reported similar issues, including weakness, low energy, feeling sleepy, and these health-related issues are due to malnutrition (Figure 4.5 in Appx.).

Stammering and hesitation in speaking are also a commonly reported disability that affects student performance. In most cases, students are being mocked have low self-esteem. Stammering disability was reported by 3.88 percent of the total disabled. Physical disability was also reported by students, which include functional disability in either arms or legs. Some of the students also report short height in this category (Figure 4.5 in Appx.). The physical disability category includes 3.88 percent of the total students the disability sample. Skin disability in reported in 0.97 percent of students is reported; therefore, skin issues are less commonly reported.

Student's characteristics also consider the birth position. Many studies suggested that the first child is likely to face more restrictions regarding the time he can spend watching TV, or playing. Further, the students also get more attention from the parents, and studies are given more time (Ha & Tam, 2011; Hotz & Pantano, 2015; Paulhus, Trapnell, & Chen, 1999).

Out of the total sample, 23.23 percent of students are the first child in the family, 56.99 percent is the middle child, and 19.78 percent of students are the youngest in their family. Ender wise disaggregation also shows that the major student in our sample is the middle child (Figure 4.6 in Appx.).

Data results also showed that the majority of the student has to face pressure from the family to perform well in their studies. Out of the total, 64.89 percent responded by answering yes, that the parents have high expectations from their children for academic achievements (Figure 4.7 in Appx.). From the figure, it can be seen that the same pattern persists in the three tehsils. The analysis also shows that only 3.83 percent of the families do not motivate their children to improve performance, whereas 86.7 percent of families motivate and provide all the available resources to improve students, performance (Figure 4.8 in Appx).

4.4.4.3 Family characteristics

To have a rough idea about the socio-economic status of the family, a different set of questions was asked. Students were asked about their family structure, monthly income, father's occupation, family values, availability of library, books, or internet as extra learning material at home and a number of teacher parents' meetings. The analysis of the data is presented with the help of visualization for a matter and clear understanding; following the cultural norms of the country, a joint family system is very common in Pakistan. Approximately 43.54 percent of the students

belong to the joint family system in district Mardan; 56.46 percent of the students live in a nuclear family system. At the tehsil level, for Takhat Bhai and Katlang, no significant difference can be seen; an approximately equal number of families' lives in joint and nuclear families (Figure 4.9 in Appx.). However, for the tehsil Mardan, a significant difference can be seen, a vast majority lives in the separately as a nuclear family (nuclear family = 39.70 percent; joint family = 27.59 percent).

The data for the monthly income and educational expenditures is also collected, based on which we can divide the students' families into four income groups. Low-income group with income below 10,000 Rs., Lower Middle-income group with a family income between 10,000 Rs - 30,000 Rs, upper-middle-income group with an income between 30, 000 Rs. – 60,000 and for high income with a monthly income above 60,000. Based on the distribution discussed above, 35.19 percent of the students belong to the low-income group, 42.03 percent of the students belong to the lower-middle-income group, 12.78 percent belong to the upper-middle-income group, and only 10 percent of the students belong to the high - income group (Figure 4.10 in Appx.).

Students were asked about their families' monthly educational expenditures. The graphical analysis shows that 65.79 percent of the students claim that their educational expenditures are below 10,000 Rs., 29.47 percent claim that their expenditures are between Rs. 10,000 and Rs. 60,000 and only a small average of 4.74 percent of students claim that the monthly family educational expenditures are above Rs. 60,000.

The educational level is also an important indicator to provide a better idea about the socio-economic status of the family. As education provides better earning opportunities and guarantee a higher annual earning (Hanushek & Raymond, 2005). However, 79.24 percent of males and 94.22 percent of female's parents have an education level equal to 10-year matriculation (metric-SSC), out of which 43.83 percent of males and 78.05 percent of the females has education below middle (Figure 4.11 in Appx.). Thus, due to the same reason, it can be seen that 16.17 percent of the males are unemployed and 21.05 percent are forced to work in elementary occupations, mostly as daily wagers. The second most common occupation in the district Mardan is service and sales (16.02 percent). Approximately 10 percent are working in agricultural lands and forestry (Figure 4.12 in App). Out of the total sample, it can be seen that around 31.88 percent males are working in professions that can guarantee a fixed monthly income, like managers (2.56 percent), professionals (10.38 percent), clerical support workers (4.71 percent), technician and associate programs (6.69 percent), armed forces, security and police force (7.44 percent). In the case of the female parents approximately, 86.84 percent are homemakers and are not part of the workforce, and only 13.16 percent are employed in professional, elementary, or other related occupations.

Higher educational opportunities that will be available to the student significantly depends on family values (Khattak, 2013). More specifically, female high education opportunities are more dependent on social norms. Thus, to investigate this aspect, a measure related to family values is added in the questioner. Overall, 68.5 percent of the families have moderate views regarding the education of their children, and they want them to continue studying at a higher level as well. Approximately 10 percent of students are of the view that their family will not support them to study more and have a conservative view (Figure 4.13 in appx.). At the same time, 21.3 percent of the students report a neutral view about educating their children (Table 4.5). If we disaggregate

the same analysis based on gender, we will observe the same view. Interestingly, it can be observed that within a female student sample, 36.77 percent claim to have moderate views compared to 31.72 percent of the male students (Figure 4.13 in Appx.). It can be concluded that in district Mardan, families are focusing equally on educating their daughters along with their sons.

Table 4. 5: Family Values

	Family Values			Total
	Conservative	Moderate	Neutral	
Female	55 (4.1)	489 (36.77)	127 (9.55)	671 (50.45)
Male	81 (6.09)	422 (31.73)	156 (11.73)	659 (49.54)
Total	136 (10.22)	911(68.49)	283 (21.27)	1330 (100)

To measure the parental support towards improving the students’ performance, they were asked if the parents help them in completing their school tasks. Out of the total, 55.79 percent of the students replied that their father helps them in completing the tasks that are assigned by teachers (figure 4.14 in Appx.). Disaggregated value response at the tehsil level shows that 10.15 percent replied “Yes” and 8.27 percent replied “No,” or tehsil Mardan 37.22 percent replied “Yes” and 30.08 percent replied “No” and for the tehsil Takht Bhai 8.42 percent replied “Yes” and 5.86 percent replied “No.” A similar question was also asked about their mother’s role in helping the school task, 45.94 percent replied “Yes” against 54.06 percent who replied “No.” disaggregated response again each tehsil is shown in the figure. Jointly, it can be seen that 68 percent of the students are those who replied that both their parents help to complete the school task. It has been stated in many research studies that the parental involvement pays a significantly positive role in the students learning (Berthelsen & Walker, 2008; LaPoint et al., 2010; Lau, Li, & Rao, 2011; Karbach et al., 2013; Castro et al., 2015). Parental involvement can take any form; it can be in

terms of providing instruction, or developing a framework for the students or even developing a habit to self-learn and discipline (OECD, 2017a).

Many researchers are of the view that at the primary level, students are provided out of the course reading material so that they can acquire reading skills; however, this practice is not common on the higher educational level. Thus, developing reading habits through a library, book, magazine, or any other reading material on the internet that can help in literacy development, creativity, and critical think skills (Erdamar & Demirel, 2009; Merga, 2015). Following Merga (2015), students were also asked about the availability of books, library or the internet at home, so that it can be used as an explanatory factor that can describe the difference in the performance (Figure 4.15 in Appx). Statistics show that 24.29 percent of the students have access to out of the course reading material, whereas 75.71 percent do not have any such opportunity.

To measure family support and engagement of parents in students' performance, they were asked about the number of visits to the school in the last 12 months. Statistics show that the majority of parents do not visit schools for parent teacher meetings. Out of the total, 12.48 percent visited once, 15.11 percent visited twice, and 9.47 visited 3 times in the last twelve months. Only 10.92 percent of parents visited more than 4 times in the last term (Figure 4.16 in Appx).

4.4.4.4 School level Characteristics

Studies revealed that geographic differences could help in achieving a variety of institutional objectives. Saurbier (2014) is of the view that the infographic is related to the critical think's skills of students, and this enhances the creativity and the non-cognitive skills that can guarantee a successful life. Additionally, the difference in the geographical location can also effectively support the reading comprehension, writing, and clarity in the understanding of the science subjects. The student performance is analyzed in the light of these geographical locations and school types, i.e., either a male school or a female school (Table 4.6). The analysis is conducted separately for these characteristics by Owoeye & Yara (2011) and finds a significant difference between the performance of rural and urban schools and suggested that the government need to reduce the gap by providing skilled teachers and more faculties.

Table 4. 6: Frequency Distribution (School Characteristics)

This table shows the frequency distribution of the sample schools selected across gender and region i.e. rural and urban.

Location	Freq.	Percent	Cum.
Rural	16	53.33	53.33
Urban	14	46.66	100
Total	1,330	100	

Type	Freq.	Percent	Cum.
Female	17	56.66	56.66
Male	13	43.33	100
Total	30	100	

4.4.5 Results and Discussion

4.4.5.1 Student Performance Analysis

Performance indicators are usually developed based on the student's outcomes, and they focus on specific program-related achievements and expectations that must be met. There are many ways discussed in previous literature through which performance can be measured. Mainly, cognitive skills are evaluated based on the knowledge, problem-solving skills, application of scientific methods, and this knowledge is used for the analysis and evaluation of the subject matter. In terms of the non-cognitive life skills, we measured effective learning, which is demonstrated by the over behavior, the individual responses, valuing, and organizing. Additionally, we considered the role of individual student effort and financial resources. Further, the learning that occurs during adolescence is incredible in the physiological, social, and cognitive domains. The selected sample shows the learning development for the science students who face challenges in learning the scientific discipline. Additionally, the learning development in students is also the reflection of the teacher's training through general teaching programs.

The current study is amongst the few of its kind that used different input and output to measure the efficiency score of the students. However, for Pakistani student data, there is a mix of evidence regarding the variables that could be chosen for the analysis. Therefore, the multivariate regression model is used, so that choose the list of input variables amongst the many available. Ordinary least square (OLS) was estimated to get the estimates. Individual student annual marks raw score is used as the proxy to measure student performance. Adjusted R-square measures variation independent variables that is explained by the independent variable is 0.194. Correlation analysis is also performed to analyze the relations between the input and output variables, low to medium level correlation was observed between the variables. The value of R-square is considered

satisfactory because heterogeneity is a common factor measured in educational studies. The coefficient of parameters selected is reported in the table, along with the t-statistics and p-value of significance.

To measure the student's ability to reason and analyze, they were given English and Urdu comprehension paragraphs, after which they had to answer some short questions. Further, out of the textbook, mathematic questions were asked to measure student's ability to use the knowledge gain in school in their daily life. Some questions were also given to measure the analytical abilities of the student. Thus, a high-test score represents a higher level of cognitive abilities. Thus, the results of this study show that cognitive abilities have a strong positive relationship with the student performance, which is measured by the 9h grade annual board results. Further, a high score in the student's cognitive abilities is also considered as the indicator of school quality and performance (Caro, Lenkeit, & Kyriakides, 2016; Hanushek & Raymond, 2005; Kyriakides, 2005).

Even though the students are provided with a supportive environment for learning, and high academic achievement is the predictor of a student's future success and earning. However, a student's attitude toward his teachers, school, peers, family, and life is considered important indicators to measure an individual's attitude. Students' attitude is measured in five different domains, using a different set of items in each domain. Self-control is the capacity to adapt and learn from the changing environment to better fit yourself in society. Thus it is considered as the key indicator for positive outcomes and productivity (Malouf et al., 2014; Zabelina, Robinson, & Anicha, 2007). It can be seen that self-control (p) has a negatively related to the annual marks, indicating that students get overconfident about their self-due to which they put less effort into the study; however, the results are not significant.

Further, educational psychologists are also of the view that too much or too little self-control could also fail to achieve the desired goals or objective (American Psychiatric Association, 2000); however, other studies do not support this analysis (Tangney, J.P., Baumeister, R.F., Boone, 2004; Tangney, Baumeister, & Boone, 2004; Zabelina et al., 2007). Negative self-perception (self-control (n)) has a significant positive effect on the performance, thus showing that the individual student is well aware of his weaknesses and strive to perform better. It can also be observed that for all the three tehsils, self-control (n) is, on average, higher than self-control (p), indicating that students doubt their abilities and lack self-confidence.

We also considered the student's behavior in terms of expressing their emotions of anger, sadness, and happiness socially. Further, positive self-perception may lead the individual to be more socially confident and hence can express their views more openly (Zabelina et al., 2007). A different set of items are included to measure if a student likes to be socially active or not. It can be seen that the social-expressivity is positively related to the performance; however, the results are not significant. Further, previous literature shows that the Students' social sensitivity can also have an impact on the performance; however, the level of sensitivity varies the effect. Smith & King (2004) are of the view that more socially sensitive students are affected more by criticism. The analysis shows that in the case of the selected sample, social sensitivity does not have any impact on the annual marks of the students. One of the reasons could be the families' social and economic status, as students are not motivated to participate in the social and leadership roles, where they get the change to polish their skills. Further, as the majority of the selected sample belong to lower- middle income group and their peers are also from the same background therefore socially sensitive do not have any significant effect on annual marks. However, it is recommended

to use the data for the schools, with low, medium and high fee groups to analyze the effect including public, private and public/private partnership schools.

Table 4.7 shows that emotional support has a negative and significant effect on the student's annual marks. In this domain, few questions were asked to observe the student's attitude when he has to face some emotional situation and how he deals with it. They were asked if they are good listeners and support their friends when he is in a problem (Table 4.7). Further, it may be the case that as teenagers, if the student is more involved in solving the problems of others, he faces difficulty in managing the study time. Conflict management skills were also measured to analyze the student's ability to deal with a difficult situation and further how it can impact his performance. In the case of our analysis, conflict management does not have any significant impact on the performance; however, it is an important domino that can guarantee lifelong learning and success.

Students' daily time allocation on different activities recorded to check the effort level/time student spends in studying. Initially, ten-items were considered; however, based on EFA items were reduced to three, i.e., time spent on self-study during weekdays, weekends, and during the exam. The average time spent has a significant positive impact on student performance. Lastly, the financial resources and a strong significant positive impact on student performance, which is adding to the existing evidence in the literature. In the current knowledge generation, the ability to adapt, learning, and implement the knowledge in daily life presents unique challenges (Table 4.7). The competition and is now even more, as the student not only has to prove their academic knowledge, but they also have to show their ability to adapt, critical thinking, and reasoning, which is the indicator of lifelong learning and success.

Table 4. 7: Regression Analysis

This table shows the results of the regression analysis, students annual marks are taken as the dependent variable and components of ability, effort and financial resources are taken as independent variables. The multivariate regression model is used, so that choose the list of input variables amongst the many available.

VARIABLES		Coefficient
Cognitive ability	Test Score	7.609*** (0.542)
Non-Cognitive Abilities/ Life Skills	Self-Control (p)	-2.838 (2.438)
	Self-Control (n)	3.952* (2.193)
	Social Expressivity	3.079 (2.112)
	Social Sensitivity	2.121 (1.969)
	Emotional Support	-4.052* (2.296)
	Conflict Management	1.112 (2.066)
Time spent on study	Effort Level	6.231*** (0.744)
Resources	Financial Resources	7.143*** (2.070)
	Constant	146.793*** (20.372)
	Observations	1,329
	R-squared	0.199

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.4.5.2 Frequency Distribution of Efficiency Components

The current DEA model is used for the analyses of the efficiency of students. Further, the selected input and output model is used to calculate the total Factor productivity that is decomposed into its efficiency components. The input variables with low to medium level correlation are included in the production model to show their relevance in achieving school level policymaking. Further, the selected production model is estimated using the variable return to scale; as a result, some students are allowed to achieve high-efficiency scores as compared to others.

This study focuses on the individual student level efficiency so that the performance issue can be studied at the micro-level that provides a clearer picture of the research objects that are being investigated. Summarized analysis of the student efficiency is presented in table 4.9 for the whole district Mardan, and further separation at the tehsil level. The table reports the results in the Output Oriented Technical Efficiency (OTE), Output Scale Efficiency (OSE), and Output Scale Mix Efficiency (OSME). The OSME can further be decomposed into mix efficiency and the residual scale efficiency (ROSE). However, as we are using only one output, i.e., student's annual board marks in 9th grade; therefore, the allocation of resources to achieve the efficient output mix cannot be applied. For the analysis, the mix efficacy, also referred to as the allocative efficiency score is 1. The frequency distribution on OTE shows that for the full student sample data, the mean score is 0.78, with a standard deviation of 0.14. The minimum technical efficiency recorded is 0.33 for the full sample. The technical efficiency of 63 percent of the student is above the mean score of 0.78, and 37 percent are below the means, showing that there is a potential to improve student performance. Further, it can be seen that only 20 percent of the students have a score higher than 0.95. Thus, suggests that educational policy needs to be reconsidered so that a min of 80 percent student should move to the high technical efficiency level.

At the tehsil level, it can be seen that the mean score of Mardan, Katlang, and Takht Bhai are 0.78, 0.81, and 0.75, respectively. Representatives that the average TE score of Katlang is highest amongst the three districts with a standard deviation of 0.11, additionally, it can be seen that 63 percent of the students score lie about the average score (Table 4.8). Whereas in the case of Takht Bhai, 53 percent of the students lie above the mean score. Therefore, to improve the performance, teachers need to focus on improving the performance and development of life skills, which can then be used to make a better decision regarding the life priorities, especially the time, effort, and resources that a student should spend on studying.

Similarly, it can be seen that the average scale efficiency at the district level and the tehsil level is above 0.94 and higher. Indicating that the maximum optimal level of efficiency score that can be achieved by the students with the given input level is much higher than what the achieved, i.e., OTE. Thus, suggesting again that the student's skills and input level indicators need to be improved. Lastly, the scale mix efficiency, thus represents the movement from the technical efficiency point to new maximum productivity; thus, an input mix of resources can help in achieving a productivity maximum point. The maximum productivity (OSME) that can be achieved if we consider the full sample is 80 percent, for tehsil Mardan it 80.7 percent, for Katlang its 81.6 percent, and lastly, it's 94.4 percent for the Takht Bhai (Table 4.8). The wider the gap between the OTE and OSME, more effort is then required to increase productivity. It can be concluded that to achieve a high level of productivity; only academic success is not enough; students should also have the affective soft skill that can guarantee his future success.

Table 4. 8: Frequency Distribution

Frequency Distribution For Technical Efficiency, Scale Efficiency And Scale Mix Efficiency (Full Sample)							Frequency Distribution For Technical Efficiency, Scale Efficiency And Scale Mix Efficiency (Mardan)					
INTERVAL	OTE		OSE		OSME=OME x ROSE		OTE		OSE		OSME=OME x ROSE	
	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE
0.30-0.35	2.00	0.15	0.00	0.00	1.00	0.08	2.00	0.22	0.00	0.00	0.00	0.00
0.35-0.40	2.00	0.15	0.00	0.00	0.00	0.00	1.00	0.11	0.00	0.00	0.00	0.00
0.40-0.45	9.00	0.68	0.00	0.00	5.00	0.38	6.00	0.67	0.00	0.00	5.00	0.56
0.45-0.50	26.00	1.95	1.00	0.08	9.00	0.68	17.00	1.90	0.00	0.00	3.00	0.34
0.50-0.55	34.00	2.56	4.00	0.30	8.00	0.60	22.00	2.46	3.00	0.34	2.00	0.22
0.55-0.60	37.00	2.78	1.00	0.08	16.00	1.20	25.00	2.79	1.00	0.11	12.00	1.34
0.60-0.65	97.00	7.29	4.00	0.30	21.00	1.58	58.00	6.48	2.00	0.22	13.00	1.45
0.65-0.70	128.00	9.62	8.00	0.60	44.00	3.31	88.00	9.83	4.00	0.45	29.00	3.24
0.70-0.75	151.00	11.35	4.00	0.30	111.00	8.35	106.00	11.84	3.00	0.34	65.00	7.26
0.75-0.80	166.00	12.48	9.00	0.68	278.00	20.90	117.00	13.07	4.00	0.45	190.00	21.23
0.80-0.85	183.00	13.76	13.00	0.98	386.00	29.02	119.00	13.30	8.00	0.89	250.00	27.93
0.85-0.90	119.00	8.95	42.00	3.16	326.00	24.51	79.00	8.83	27.00	3.02	228.00	25.47
0.90-0.95	97.00	7.29	208.00	15.64	110.00	8.27	67.00	7.49	132.00	14.75	85.00	9.50
0.95-1.00	279.00	20.98	1036.00	77.89	15.00	1.13	188.00	21.01	711.00	79.44	13.00	1.45
TOTAL	1330.00	100.00	1330.00	100	1330.00	100.00	895.00	100.00	895.00	100	895.00	100.00
Mean (SD)	0.7813 (0.14)		0.9616(0.05)		0.8015(0.08)		0.7822 (0.14)		0.9641(0.05)		0.8071(0.08)	

Frequency Distribution For Technical Efficiency, Scale Efficiency And Scale Mix Efficiency (Katleng)							Frequency Distribution For Technical Efficiency, Scale Efficiency And Scale Mix Efficiency (Takht Bhai)					
INTERVAL	OTE		OSE		OSME=OME x ROSE		OTE		OSE		OSME=OME x ROSE	
	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE	FREQUENCY	PERCENTAGE
0.30-0.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.41
0.35-0.40	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.41	0.00	0.00	0.00	0.00
0.40-0.45	0.00	0.00	0.00	0.00	0.00	0.00	3.00	1.22	0.00	0.00	0.00	0.00
0.45-0.50	0.00	0.00	0.00	0.00	0.00	0.00	9.00	3.67	1.00	0.41	6.00	2.45
0.50-0.55	1.00	0.53	0.00	0.00	0.00	0.00	11.00	4.49	1.00	0.41	6.00	2.45
0.55-0.60	1.00	0.53	0.00	0.00	0.00	0.00	11.00	4.49	0.00	0.00	4.00	1.63
0.60-0.65	10.00	5.26	0.00	0.00	1.00	0.53	29.00	11.84	2.00	0.82	7.00	2.86
0.65-0.70	14.00	7.37	0.00	0.00	3.00	1.58	26.00	10.61	4.00	1.63	12.00	4.90
0.70-0.75	21.00	11.05	0.00	0.00	18.00	9.47	24.00	9.80	1.00	0.41	28.00	11.43
0.75-0.80	22.00	11.58	1.00	0.53	37.00	19.47	27.00	11.02	4.00	1.63	51.00	20.82
0.80-0.85	44.00	23.16	0.00	0.00	60.00	31.58	20.00	8.16	5.00	2.04	76.00	31.02
0.85-0.90	24.00	12.63	6.00	3.16	54.00	28.42	16.00	6.53	9.00	3.67	44.00	17.96
0.90-0.95	17.00	8.95	31.00	16.32	16.00	8.42	13.00	5.31	45.00	18.37	9.00	3.67
0.95-1.00	36.00	18.95	152.00	80.00	1.00	0.53	55.00	22.45	173.00	70.61	1.00	0.41
TOTAL	190.00	100.00	190.00	100	190.00	100.00	245.00	100.00	245.00	100	245.00	100.00
Mean (SD)	0.8182 (0.11)		0.9722 (0.03)		0.8169 (0.05)		0.7507 (0.16)		0.9441 (0.08)		0.7701 (0.10)	

4.4.5.3 Total Factor Productivity and Its Components

The current model is based on the output-oriented production function, which is based on the concept of increasing the output with the given level of inputs. In other words, the optimal use of inputs that can increase the outputs. The student-level TFP and its components are then aggregated at the school level to present the overall summary so that the performance can be analyzed. The analysis in this section helps to understand how efficiency the schools are? Further, how much improvement each school can achieve. The table shows in detail the Total Factor Productivity (TFP) of each school is represented in column 1 of the table. The mean TFP is 0.5306 with is far below the maximum optimal, i.e., 0.8484 that can be achieved.

Approximately 60 percent of schools have productivity above the mean TFP, and 40 percent lies below the mean average (underperforming schools). The highest productivity observed is for GGHS Lund Khwar, i.e., 0.6189 and GGHSS no. 1 Mardan, i.e., 0.6157, whereas the lowest productivity was recorded for GHS Sawal Dher, i.e., 0.4144 (Table 4.9). Further, if we look at the TFP efficiency, which is calculated by dividing TPF/TFP* also shows the same results. The TFP is decomposed into TPF*, OTE, OME, and ORSE; however, it can be seen that the OME³⁸ is one and ROSE represent the residual factor; therefore, the main contributor is the output technical efficiency. Consider GGHSS no. 1 Mardan the $TFP = TPF^* \times OTE \times OME \times ROSE$ is $0.6157 = 0.8484 \times 0.8847 \times 1 \times 0.8203$. The results show that none of the schools in the selected sample reach the full efficiency level. The highest efficiency level is again for the GGHSS no. 1 Mardan is 88 percent, which still shows the potential of improvement. Further, 13 schools of the total show an

³⁸ OME is one as we are considering only one output, in case of multiple outputs it represents the resource mix i.e. how the resources can be allocated between two outputs, so that TFP can be improved (economies of scope).

efficiency level above 80 percent. The lowest technical efficiency is reported for GHS Labour Colony, i.e., 0.6101.

The table also 4.9 reports the results of the output scale efficiency, which shows the maximum optimal efficiency that can be achieved with the given resources. On average, the maximum efficiency that can be achieved by using the inputs efficiently is 96 percent, which is 8 percent more than what is currently being achieved (Table 4.9). Output scale mix efficiency represents the maximum total productivity that can be achieved; this is using the concept of both economies of scale and scope.

The only cost variable selected in this study is the financial resources, whereas the majority are non-cost variables (Rutter & Maughan, 2002). Therefore, schools do not have control over these input factors; thus, they can be explained by other factors like school location. The finding of this section is the same as that was observed during the survey; the schools with highest TPF and OTE is also the one that performed well in the annual board exam.

Table 4. 9: School Level TFP and efficiency Components

This results in this tables shows the TFP and its components for all the schools selected in sample. The highest and the lowest values are showed in bold.

	Schools	TFP	TFP*	TFPE	OTE	OSE	OME	ROSE	OSME
1	GCMHS, NO.3 MARDAN	0.5825	0.8484	0.6866	0.8423	0.9589	1.0000	0.8150	0.8150
2	GGCHMHSS CANAL ROAD MARDAN	0.5763	0.8484	0.6793	0.8551	0.9771	1.0000	0.7944	0.7944
3	GGHS GHARI DOLAT ZAI	0.5574	0.8484	0.6571	0.7493	0.9815	1.0000	0.8770	0.8770
4	GGHS KHAZANA DHARE	0.5668	0.8484	0.6681	0.8227	0.9836	1.0000	0.8121	0.8121
5	GGHS LABOUR COLONY	0.5503	0.8484	0.6486	0.8039	0.9728	1.0000	0.8068	0.8068
6	GGHS LUND KHWAR	0.6189	0.8484	0.7296	0.8818	0.9773	1.0000	0.8274	0.8274
7	GGHS MAHODHERI	0.5678	0.8484	0.6693	0.8269	0.9712	1.0000	0.8094	0.8094
8	GGHS MANGA MARDAN	0.5844	0.8484	0.6888	0.8285	0.9762	1.0000	0.8314	0.8314
9	GGHS MAYAR	0.4725	0.8484	0.5569	0.7391	0.9522	1.0000	0.7535	0.7535
10	GGHS SCHOOL BAKRI BANDA	0.5779	0.8484	0.6812	0.8020	0.9632	1.0000	0.8494	0.8494
11	GGHS SERI BEHLOL	0.5344	0.8484	0.6299	0.7615	0.9607	1.0000	0.8271	0.8271
12	GGHS WARD NO. 4	0.5669	0.8484	0.6682	0.8341	0.9715	1.0000	0.8011	0.8011
13	GGHSS NO.1 MARDAN	0.6157	0.8484	0.7257	0.8847	0.9682	1.0000	0.8203	0.8203
14	GGHSS RUSTAM KHEIL	0.5493	0.8484	0.6475	0.8116	0.9656	1.0000	0.7978	0.7978
15	GGHSS SAWAL DHER	0.5424	0.8484	0.6393	0.7788	0.9736	1.0000	0.8209	0.8209
16	GGHSS SHAH DAND BABA	0.4571	0.8484	0.5388	0.6798	0.9474	1.0000	0.7926	0.7926
17	GGHSS TORU	0.4947	0.8484	0.5832	0.7034	0.9610	1.0000	0.8291	0.8291
18	GHS GARHI DAULAT ZAI	0.5272	0.8484	0.6215	0.7901	0.9683	1.0000	0.7866	0.7866
19	GHS KHATLANG	0.4742	0.8484	0.5590	0.7487	0.9407	1.0000	0.7466	0.7466
20	GHS KHAZANA DHERI	0.5755	0.8484	0.6784	0.8421	0.9844	1.0000	0.8064	0.8064
21	GHS LABOUR COLONY MARDAN	0.4202	0.8484	0.4953	0.6101	0.9338	1.0000	0.8119	0.8119
22	GHS NO. 1 LUND KHWAR	0.6033	0.8484	0.7112	0.8616	0.9531	1.0000	0.8254	0.8254
23	GHS SARI BHALLOOL	0.5324	0.8484	0.6275	0.7709	0.9741	1.0000	0.8140	0.8140
24	GHS SAWAL DHER KATLANG	0.4144	0.8484	0.4884	0.6588	0.9213	1.0000	0.7414	0.7414
25	GHS TORU	0.4948	0.8484	0.5833	0.7334	0.9472	1.0000	0.7953	0.7953
26	GHSS CHAMTAR	0.5457	0.8484	0.6432	0.7844	0.9449	1.0000	0.8200	0.8200
27	GHSS MANGA MARDAN	0.5077	0.8484	0.5985	0.7573	0.9681	1.0000	0.7903	0.7903
28	GHSS MAYAR	0.4776	0.8484	0.5629	0.7475	0.9563	1.0000	0.7652	0.7652
29	GHSS MOHABAT ABAD	0.5432	0.8484	0.6403	0.7847	0.9778	1.0000	0.8160	0.8160
30	GHSS SHAH DAND BABA	0.4706	0.8484	0.5547	0.7022	0.9507	1.0000	0.7993	0.7993
	Mean	0.5306	0.8484	0.6255	0.7771	0.9626	1.0000	0.8056	0.8056
	Min	0.4144	0.8484	0.4884	0.6101	0.9213	1.0000	0.7414	0.7414
	Max	0.6189	0.8484	0.7296	0.8847	0.9844	1.0000	0.8770	0.8770

The technical score analysis indicated that GGHS Lund KHwar and GGHSS No.1 Mardan are amongst the top-performing schools, whereas GHS Sawal Dher Katlang and GHS Labour Colony Mardan are amongst the underperforming schools. The similar way the mean annual marks and the cognitive score is also shown in the table below. Overall mean annual marks are 340 for the full sample. However, mean annual marks for males, i.e., 322 is lower than the female, i.e., 358. For the tehsil level analysis, the mean annual score in Mardan for males is 325, and for females, it is 356; for Takht Bhai, the mean annual score for males is 350, and for females is observed as 365.

For the tehsil Katlang on average, males have 311 marks, and female students scored 357. Overall, it can be seen that tehsil Takht Bhai student scored, on average, higher marks than the other district, and GGHS Lund Khwar also belongs to the same district.

If we analyze the Cognitive Ability that was measured through the test score, the overall mean score is reported to be 12.68 or 13. The mean score for males is 12.11, and for females, it is 13.25, further, at the tehsil level Mean score in Mardan for males is 12.53 and for females is 13.40. The mean score in Takht Bhai for males is 12.50 and for females is 12.84. The mean score in Katlang Bhai for males is 11.17, and for females, it is 13.17. Amongst the underperforming schools GHS Sawal Dher Katlang, GHS Labour Colony Mardan, and GHS Khatlang. Some studies suggested that competition among the school can reduce the number of underperforming schools (Gill & Booker, 2014; C. M. Hoxby, 2005; Jaag, 2011).

Teachers' behaviors may also explain the difference in student performance (Den Brok, Brekelmans, & Wubbels, 2004; Wei, Den Brok, & Zhou, 2009). However, in another study, no significant change was observed in student outcomes after one year of the teacher's professional development and suggested further investigation (Antoniou & Kyriakides, 2013). It was also observed that the teacher in top-performing schools was more friendly towards the students, and in one of the underperforming schools, the attitude was quite different.

As the inputs used in this study are not being investigated before for Pakistan, therefore, teacher's training should be the focus on developing the non-cognitive skills in students, and the efficiency level should be measured again for any impact. Further, overtime analysis of the performance comparison can also provide insight into the areas in the school education that need improvement. Moreover, the performance analysis of the students is considered at the Mardan

district level (Meta-frontier); further, a separate analysis for each tehsil can better help to understand the reason for the difference in the school performance. Further, the difference in the geographical, social, and economic factors of the school tehsil can also be a contributing factor.

4.4.5.4 Factors Contributing to the Change in The Technical Efficiency

To investigate the factors that can be a cause to explain the differences in the efficiency score, the Tobit regression model was estimated. One of the main reasons for the difference in the efficiency score could be the input variables choose. Badri & Mohaidat (2014) are of the view that different input variables should be chosen to estimate the difference in the efficiency score. Thus, the model comparison can also guide policy makers regarding the variables that matter the most in improving efficiency. However, some factors are not in control of institutions, which can be a contributing factor. Therefore, this section main explores those factors. There are pros and cons of using two stay DEA models; however, when the model is complex and too many influencing factors are involved, it's better to use this model. Halkos, Tzeremes, and Kourtzidis, (2015) suggested to use the additive two-stage DEA model, that can be one of the extensions for future research. The Tobit model is used in the second stage as the technical efficiency score of student performance is bounded from above, and OLS regression provides inconsistent estimates.

Table no. 4.10 shows the Tobit model results for individual attributes of the selected students³⁹. Overall, model findings show that gender and family pressure on students to improve performance have a significant technical efficiency (Table 4.10). Regardless of gender, students

³⁹ Note: The results are represented in terms of thousands of unit.

from any social-economic background have to face emotional pressure for achievement (Weissbourd, 2011). It can be seen from the results that any additional pressure from the family motivates the student to improve its technical efficiency by investing more effort towards studies; however, the magnitude of the effect is too small. Through analysis of the data is for the majority of the family belong to low or lower-middle-income group, that could explain the small effect size, however to the family that invests more in terms of financial resources and opportunities, leads to higher pressure on the student end (Z. Li & Qiu, 2018).

Age, disability, and ethnicity were also recorded; however, its effects of these variables are not significant, except for the few outliers it can be observed from the descriptive statistics discussed earlier that not much variation could be observed (Table 4.10). The position of childbirth is considered, and the contribution factor the success and achievement (Ha & Tam, 2011; Hotz & Pantano, 2015; Paulhus et al., 1999). However, the data for the selected sample does not support this phenomenon. Likewise, Leong et al. (2001) also report similar results. However, these findings are specific for the Mardan district and cannot be generalized, and further supporting evidence is needed.

Table 4. 10: Tobit Model Results (Individual Student Attributes)

	Variables	1 Model
Gender	Male	-0.058***
		(0.009)
	Age	-0.007
		(0.005)
	Disability	0.007
		(0.016)
	Number of Siblings	-0.000
	(0.002)	
Ethnicity	Urdu Speaking	0.081
		(0.120)
	Punjabi Speaking	-0.065
		(0.199)
	Sindhi Speaking	0.114
		(0.163)
	Pushto Speaking	0.107
		(0.115)
Position of Birth	Balochi Speaking	0.187
		(0.168)
	First Child	0.005
		(0.014)
	Middle Child	0.003
		(0.012)
	Family pressure to improve performance	0.016*
		-0.01
	Constant	0.825***
		(0.137)
	Sigma	0.162***
		(0.004)
	Observations	1,330

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Many studies available used the social-economic background of the family to explain the differences in performance. This section used the technical efficiency score as the dependent variable and set of family characteristics as the independent variables (Model 2). It is generally accepted that the family background plays a very important role in defining student success. Further, parental involvement and support are also major contributing factors (Griffith, 1996; Barge & Loges, 2003; Topor, Keane, Shelton, & Calkins, 2010; McNeal, 2015). Family structure does not show any impact of the technical efficiency (Table 4.11). Moreover, a small effort side

can be seen (Ndyabawe, 2016). However, family size and the number of schools going have a significant effect on performance. As the number of family member increases the technical efficiency, decrease by a magnitude of 0.002 as the limited financial resource needs to be divided amongst the family members. However, a positive increase in technical efficiency is observed due to one additional school going child, showing a significant peer effect. Additionally, it provides a better learning environment that can improve technical efficiency (Arif, 2015). Considering the family income, it can be seen that the students who belong to the lower-middle-income group perform better than the low-income group (Table 4.11).

Moreover, for the upper-income group, the results are not significant. If we consider the combined effect of the father's educational level and occupation, it was observed child's whose father's education level is 12 years and above and also the job of household head belongs to any professional occupation, then they perform better than the others. In the case of the Mardan district, no clear evidence was found to support the fact that parental occupation is the key indicator to explain the change in technical efficiency.

The social-economic status of the family is also an indicator of the opportunities that they can provide for their children, as the availability of reading material, books, and internet resources (not significant in our case). De Witte and Kortelainen (2017) and Agasisti (2014) shows that the students perform better with more resources like internet, while this culture is not common in developing country like Pakistan. Further, the involvement of parents, specifically fathers, has an adverse effect on the performance, thus has a negative effect on academic socialization (Castro et al., 2015; Karbach et al., 2013; Lau et al., 2011; OECD, 2017b). We found the students whose parent's visit the school are underperforming compared to those students who reported no visit in the last 12 months (Table 4.11). These results are against the literature earlier which shows that

more parental involvement, improves students results (Mancebón and Mar Molinero,2000; Muñiz, 2002; Thieme et al., 2012; Agasisti (2013); Deutsch et al.,2013; Cordero- Ferrera et al., 2015). It's a case of district Mardan it can be seen that the parents are only called to visit the school in case the student has not achieved the desired outcome, however for the majority student in government sector parent's teacher meeting is not mandatory.

School location and type are also considered by many students to examine the differences in performance (Barrow, 2006; Müller, Haase, & Kless, 2009; Owoeye & Yara, 2011). Restating that these factors are not in control of an individual; however, it can be seen that the urban schools perform better than rural schools; however, the difference in terms of magnitude is low (Table 4.12). Urban educational instate achieve better results and reduce the cost (Barrow (2006), Agasisti (2011a) (2013), Lee (2011), Haelermans and Blank (2012), Haelermans and DeWitte (2012), Haelermans et al (2012),Misra et al (2012), Burney et al (2013), Deutsch et al (2013), Cordero- Ferrera et al (2015). Overall, the technical efficiency of the student in the female school is better than the male schools (Model 3)⁴⁰. It can be concluded that the family characters are the major contributing factor to explain the technical efficiency differences, thus by improving it, we can improve the average efficiency from 77 percent to an optimal high of 96 percent using the same level of inputs. Further, this improvement is reflected in terms of increased productivity at the school level.

⁴⁰ Model 4 and 5 is available in the appendix that combines all the variables in model 1, model 2 and model 3. Model 4 also reports similar finding that are presented in this section.

Table 4. 11: Tobit Model Results (Family Characteristics)

	Variables	2	
		model	
Family Structure	Joint Family	-0.006 (0.011)	
	Total Number Of Family Members	-0.002** (0.001)	
Family Income	Number Of School Going Children	0.008*** (0.002)	
	Lower Middle Inocme Group	0.029*** (0.010)	
	Upper Middle Inocme Group	0.021 (0.016)	
	Upper Income Group	0.002 (0.017)	
Father Education	Fedu Matric	0.013 (0.011)	
	Fedu Fa Fsc	0.027* (0.016)	
	Fedu Ba	0.049** (0.022)	
	Fedu Ma	0.099*** (0.026)	
	Managers	0.062 (0.042)	
Father Occupation	Professional	0.058* (0.034)	
	Technicians And Associate Professionals	0.045 (0.035)	
	Clerical Support Workers	0.053 (0.037)	
	Service And Sales Workers	0.044 (0.032)	
	Service And Sales Workers	0.053 (0.033)	
	Craft And Related Trades Workers	0.046 (0.039)	
	Elementary Occupations	0.043 (0.032)	
	Armed Forces/Security/Police Occupations	0.026 (0.034)	
	Unemployed	0.037 (0.032)	
	Father Help In Completing School-Related Tasks	-0.020** (0.010)	
	Availability Of Internet/Books/Library At Home.	-0.011 (0.011)	
	Parental visit to school.	Visit 1 To 3	-0.030*** (0.010)
		Visit 4 To 8	-0.014 (0.015)
		Visit 9 To 13	-0.052** (0.024)
Constant		0.755*** (0.032)	
	Sigma	0.161*** (0.004)	
	Observations	1,330	

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4. 12: Tobit Model Results (School Characteristics)		
	Variables	3 model
School Location	Urban	0.026*** (0.009)
	Male school	-0.058*** (0.009)
Constant	Constant	0.822*** (0.008)
	Sigma	0.162*** (0.004)
	Observations	1,330

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

4.5 Conclusion

In the knowledge-based economy, education is considered as the key factor that can guarantee the country's economic growth and development. This analysis provided gives empirical evidence that probably good academic performance associates with good future opportunities. Student performance is measured based on its ability, effort, and resource allocation (Financial resources). The student's ability is measured based on cognitive skills, and affective /non-cognitive/life skills used different sets of questions. The effort level is the time that is allocated towards studying, represented in minutes. Lastly, student educational expenditures are used as a proxy to measure the available financial resources. Data for the analysis was taken from 30 schools in district Mardan, through which responses of 1330 students were collected.

Ordinary least square method is used to investigate the relationship between the selected dependent and independent variables. The results conclude that cognitive ability, self-control (n), emotional support, effort level, and financial resources are the contributing factors for the improved student's annual marks. Further, life skill domains show, on average, a very low score,

indicating that teachers and family should spend more time in the development of these skills. Literature provides empirical evidence that these soft skills are the means for success in the current scenario; therefore, policymakers must consider it to improve the overall success in the education sector.

Further, using the non-parametric DEA model efficiency score of the individual student was obtained to analyse their performance. DPIN software was used to calculate the total factor productivity of each student, and it as further decomposed into its efficiency components. The results show that, on average, only 20 percent of the students lie in the efficiency interval of 95 percent and above. Similar results were also seen as the tehsil level analysis. Results are aggregated at the school level to provide a clearer picture of efficiency and under-performing schools. Only two schools were found to have total factor technical productivity above 60 percent, and the mean school efficiency is observed to be 53 percent. Thus, there is potential to improve the overall performance of the school in the Mardan district by reconsidering the policies that are implemented. Moreover, this study also provides insight into the maximum optimal efficiency levels that can be achieved by using the same resources. In this regard, it can be seen that there is a large room for improvement, and the government needs extensive public policy effects to improve the educational outcome and performance.

The factors that can explain the differences in the efficiency score of students mainly include gender effect, parental pressure, family size, family income, number of school-going children, father education, parental involvement and number of visitors to the school. Many other variables that were suggested through the literature were used, but no significant effect was found like age, disability, ethnicity, family structure, mother education, occupation, availability of additional learning resources. A significant difference in the performance of rural and urban

schools can be found; this gap in the policy needs to be reduced. The findings of this study are only applicable to government schools of district Mardan and cannot be generalized.

The findings of this study contribute to the existing evidence in the literature to support the role of family background in education. Findings are also evident that we need improvement at the school and family level both. The institutional environment should encourage children to develop an interest in learning habits. Teachers should be provided training on how they can guide students to deal with different situations they face during the academic year. Life and career counselling should be available at school. The government should invest in lifelong learning programs so that when the student is part of the job market, they can lead a successful life. Rather than forcing a curriculum for children should be provided with the necessary skills that are needed for a better life and empower them by giving the confidence to find their own path

Based on the current scenario, it is recommended to measure the average efficiency of the selected school sample after COVID-19 and analyse the change in performance. Higher education commissions of Pakistan incentive to launch an online lecture on the curriculum for the 9th and 10th grade, does it have any impact on efficiency? Was the government able to maintain the same efficiency level at min, or if efficiency decreased due to COVID-19, then how much decline was observed?

Another life skill that needs to be developed is stress management, many researchers have highlighted the need during the current situation, and its effect on performance needs to be examined. Additionally, the pandemic also highlighted the need for self-discipline, which is a proxy for students' effort and time they spent towards studying during home-schooling. Self-discipline could also be a key indicator of improved learning outcomes. Further, parental support

for learning before and after the 2020 pandemic and its impact on performance can also be an interesting topic of research. Further, it is also recommended extending this analysis to different districts so that the findings could be generalized.

CHAPTER 5

CONCLUSION

5.1 Concluding Remarks and Way Forward

Improving educational outcomes are a priority in most developing countries as it promotes economic growth and general welfare in society. This is why significant resources are being invested to improve educational outcomes in developing countries. This increased focus has resulted in an increase in enrolment in primary education with the objective of providing quality education to the masses. Many studies point to the role of education policies in improving learning outcomes, attendance and enrollment. But this study focuses on how resources invested in education can be used effectively to improve learning outcomes. Given that resources are scarce and the opportunity cost related to resource utilization, this study is intended to help decision makers make better and more effective resource allocation plans.

Analysis of school efficiency/performance is a wide research area covering different issue and the level of investigation. The study discusses the concept of school efficiency measurement using a productivity model. This thesis deals with the concept “efficiency” at three different levels. Overall, this study consists of three essays that relate to the area of efficiency in school education.

The first essay is related to efficiency maximization at the school and individual levels. Thus, highlights and emphasize on the fact that the available resources should be used optimally. The major question raised is on the optimal level of the student’s abilities, effort level, and resources, with a given set of constraints like budget, time, and ability. A comprehensive discussion of existing literature is also available on how these indicators affect the overall performance in the economic relevant setting. Further, this study also discusses the cost benefit analysis to obtain optimal levels of input resources at the individual student level that maximizes

the outcomes. Similarly, at the school level the outcome maximization depends on the portion of resources spent on teaching to achieve the optimal resource level leading to maximization of social welfare. The modelling of this scenario provides the much-needed guideline to policy makers so that they can make optimal allocation of available resources.

The second essay focuses on the regional level of analysis and the efficiencies for the selected district, while considering the district-controlled variables like population density, Health index, education index and living standard, along with the control variable for location and total number of primary schools. The total factor productivity of many high performing districts shows that they used the input resources efficiently to maximize the output. In literature many inputs, variable is used to calculate the production function, however, data limitations is always an issue in developing country data. Following O'Donnell, (2008) total factor productivity, efficiency is calculated and then decomposed into its technical efficiency, mix efficiency and residual scale efficiency. The results thus show that the health and education have a significant positive effect on the school efficiency. Whereas living standard has a significant negative effect on the performance. High Population density does play negative role in achieving optimal level of productivity. It is evident from results that district location in the urban or rural geography do not have any effect on the efficiency score of the district. Findings from the study suggest that student enrollment and retention in the district can be improved by providing a better learning environment, access to education and health facilities.

Further, this research motivates us to investigate the allocation patterns that maximize the individual district level efficiency in education. Thus, investigates the role of the student's ability, effort level, and financial resources available to him on educational outcomes. This study uses the production and efficiency theory to evaluate the student performance. Individual pupil efficiency

is aggregated at school level and thus the results show a difference in the performance of urban and rural schools. Further, only two schools show the total factor productivity above 60 percent, and indicate a room for improvement. Thus, the policy makers should make efforts in terms of training the existing resources to improve the productivity. Regular training to improve the teaching methods and refresher courses at regular intervals can help to improve the technical efficiency and thus the productivity. The teacher training covering how they teachers guide students to deal with different situations they face in life during the academic year can also help improve student performance. Also, Life and career counselling should be available at school.

5.2 Policy Implication

Many studies focus on student performance in the case of Pakistan; however, only a few looks at the effective use of resources to improve student performance. According to a study by the Organization for Economic Co-operation and Development (OECD, 2007), 30.7 percent of the resources allocated to the education sector can be reduced in OECD countries. Still, the same level of educational outcome is achieved. Therefore, we should also focus on using existing resources effectively rather than requiring more resources to improve outcomes.

- This conclusion from the theoretical model assists in making decisions on education spending. Districts with fully utilized resources should be provided additional recourse to improve performance, and vice versa.
- At international level, decision-makers focus on resource planning and public management, as a significant proportion of public expenditure is devoted to education. However, Pakistan still needs to focus on resource planning and develop a standard framework to measure the efficiency of the education sector on which public resources can be managed.

- Governments should focus on improving the learning environment in order to improve retention. Because of social and economic barriers, disadvantaged students are less likely to succeed in school. Thus, a better learning environment and teacher support can improve their performance.
- The difference in district level development indicators such as health and standard of living is visible in the school's efficiency as well. These differences should also be considered while allocating educational resources.
- Teacher training with a specific focus on the teaching methods is necessary to improve technical efficiency. They will lead to improvements in student and school performance.
- Reconciling professional autonomy and a collaborative culture between teachers and students is required. It can help the student improve his self-confidence, self-esteem, social sensitivity, and thus build a great leader for the future.
- Development of the student's soft skills is a new research area suggested in the study that needs focus and attention. This study shows that the non-cognitive skills have considerable effect on student performance. Research is still required to determine which soft skills will be necessary for child development and will have lasting effects.
- Time and stress management skills are also oriented towards educational research. Policymakers should consider offering free short courses for students to tackle this issue. Learning in a friendly environment needs to be encouraged.

5.3 Limitations of the Study

Based on the limited time available to complete the degree, this study cannot consider all the factors that influence the efficiency in education. However, the major constraint is the availability of reliable and updated data for the analysis.

Although a detailed theoretical model is solved to measure the optimal level of ability, effort and financial resource, however, this model cannot be empirically tested because of limitation of data availability for the coefficient used. Elasticities to the response for student ability, effort level, governmental resources spending and outcome with respect to exogenous variables like student characteristics, family status, parental influence, school administration, teaching quality and other can be analyzed.

The analysis in Chapter 3 can be extended by using panel data to explain the determinants of change in efficiency. However, for the district-level variable, there is a serious limitation in the availability of data, due to which the sample size selected is small. In a discussion by Tessema, G. A et al. (1995)⁴¹, Under normally distributed errors, the tobit MLE performed better than both the H2S estimator and Powell's LAD estimator. The latter two appeared to be biased in small samples sizes, although the bias shrinks quickly in large samples. The Tobit model uses MLE to estimate both β and σ for this model. However, there are other limitations for the implementation of tobit model.

Additionally, accepting the fact that each student is different from others based on his/her abilities, effort, opportunities, and other factors. We cannot deal with each student in the same way. As a result, much work is needed to explore the role of cognitive and emotional skills in student performance.

Furthermore, research can also adopt different educational psychology tools to measure cognitive and emotional competencies. Separate studies may be carried out on each type of skill

⁴¹ Tessema, G. A., Griffiths, W. E., & Doran, H. (1995). The Finite Sample Properties of the Estimators of the Tobit Model: A Monte Carlo Study.

and the results may help to better understand the student's constraints that actually affect performance.

Further, the same analysis can be applied at the higher education level, as many students are unable to complete their studies because of issues of time management, communications gap, self-control, social skills and lack of conflict management approach. Similar analysis can be implemented to other developing countries where majority of the students belong to rural areas.

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APPENDIX A

Table no.1: Marital Status by Tehsil

	Tehsil			Total
	Mardan	Takht Bhai	Katlang	
Married	2	1	0	3
Un-married	893	189	245	1327
Total	895	190	245	1330

Table no 2.: Religion by Tehsil

	Tehsil			Total
	Mardan	Takht Bhai	Katlang	
Muslims	893	190	245	1328
Christian	2	0	0	2
Total	895	190	245	1330

Table no.3: Ethnicity/Region of Origin by Tehsil

	Tehsil			Total
	Mardan	Takht Bhai	Katlang	
Urdu	15	6	1	22
Punjabi	1	0	0	1
Sindhi	0	0	2	2
Pushto	876	183	242	1301
Balochi	2	0	0	2
others	1	1	0	2
Total	895	190	245	1330

Table no.4: Tobit Model Results

	Variables	1	2	3	4	5
		model	model	Model	model	model
Gender	Male	-0.058***				
		(0.009)				
	Age	-0.007				-0.005
		(0.005)				(0.005)
	Disability	0.007				0.003
		(0.016)				(0.016)
	Number of Siblings	-0.001				0.001
		(0.002)				(0.002)
Ethnicity	Urdu Speaking	0.081				0.078
		(0.120)				(0.118)
	Punjabi Speaking	-0.065				-0.098
		(0.199)				(0.197)
	Sindhi Speaking	0.114				0.103
		(0.163)				(0.161)
	Pushto Speaking	0.107				0.121
		(0.115)				(0.113)
	Balochi Speaking	0.187				0.226
		(0.168)				(0.166)
Position of Birth	First Child	0.005				-0.003
		(0.014)				(0.015)
	Middle Child	0.003				0.000
		(0.012)				(0.012)
	Family pressure to improve performance	0.016*				0.018*
		-0.01				(0.010)
Family Structure	Joint Family		-0.006		-0.001	-0.000
			(0.011)		(0.011)	(0.011)
	Total number of family members		-0.002**		-0.002*	-0.002**
			(0.001)		(0.001)	(0.001)
	Number of school-going children		0.008***		0.007***	0.007***
			(0.002)		(0.002)	(0.002)
Family Income	lower middle income group		0.029***		0.027***	0.026**
			(0.010)		(0.010)	(0.010)
	upper middle income group		0.021		0.014	0.015
			(0.016)		(0.015)	(0.015)
	upper income group		0.002		-0.003	-0.003
			(0.017)		(0.016)	(0.016)
Father Education	fedu_matric		0.013		0.007	0.007
			(0.011)		(0.011)	(0.011)
	fedu_fa_fsc		0.027*		0.021	0.021
			(0.016)		(0.016)	(0.016)
	fedu_ba		0.049**		0.041*	0.044**
		(0.022)		(0.021)	(0.022)	
	fedu_ma		0.099***		0.095***	0.093***
			(0.026)		(0.025)	(0.026)
Father Occupation	Managers		0.062		0.052	0.058
			(0.042)		(0.042)	(0.042)
	Professional		0.058*		0.051	0.054
			(0.034)		(0.034)	(0.034)
	Technicians and Associate Professionals		0.045		0.044	0.047

			(0.035)		(0.034)	(0.034)
	Clerical support workers		0.053		0.049	0.050
			(0.037)		(0.036)	(0.036)
	Service and Sales Workers		0.044		0.037	0.039
			(0.032)		(0.032)	(0.031)
	Service and sales workers		0.053		0.050	0.054
			(0.033)		(0.033)	(0.033)
	Craft and related trades workers		0.046		0.032	0.031
			(0.039)		(0.038)	(0.038)
	Elementary Occupations		0.043		0.035	0.038
			(0.032)		(0.031)	(0.031)
	Armed forces/security/police occupations		0.026		0.025	0.026
			(0.034)		(0.034)	(0.034)
	Unemployed		0.037		0.031	0.032
			(0.032)		(0.032)	(0.032)
	Father help in completing the school-related task		-0.020**		-0.020**	-0.023**
			(0.010)		(0.010)	(0.010)
	Availability of internet/books/library at home.		-0.011		-0.016	-0.016
			(0.011)		(0.011)	(0.011)
Parental visit to the school.	visit 1 to 3		-0.030***		-0.023**	-0.023**
			(0.010)		(0.010)	(0.010)
	visit 4 to 8		-0.014		0.005	0.008
			(0.015)		(0.015)	(0.015)
	visit 9 to 13		-0.052**		-0.025	-0.023
		(0.024)		(0.024)	(0.024)	
School Location	Urban			0.026***	0.029***	0.029***
				(0.009)	(0.009)	(0.009)
School Type	Male school			-0.058***	-0.048***	-0.050***
				(0.009)	(0.010)	(0.010)
	Constant	0.825***	0.755***	0.822***	0.769***	0.708***
		(0.137)	(0.032)	(0.008)	(0.032)	(0.138)
	Sigma	0.162***	0.161***	0.162***	0.159***	0.158***
		(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
	Observations	1,330	1,330	1,330	1,330	1,330

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figures Chapter 4

Figure 4. 5: Disability by Type

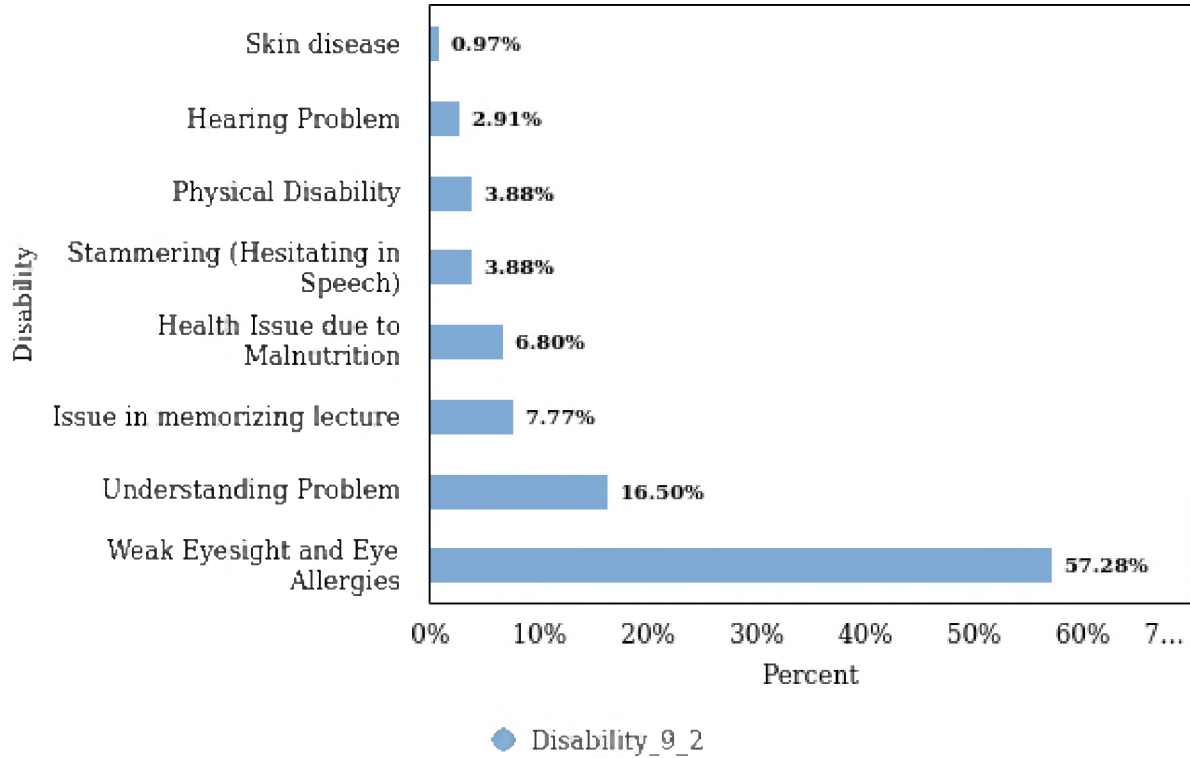


Figure 4. 6: Birth Position by Gender

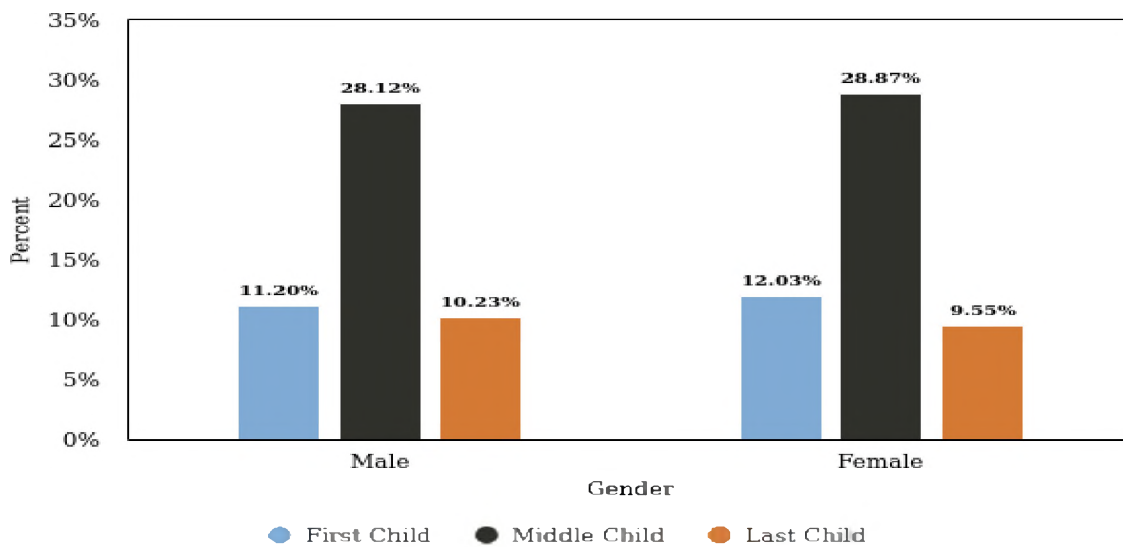


Figure 4. 7: Family Pressure by Tehsil

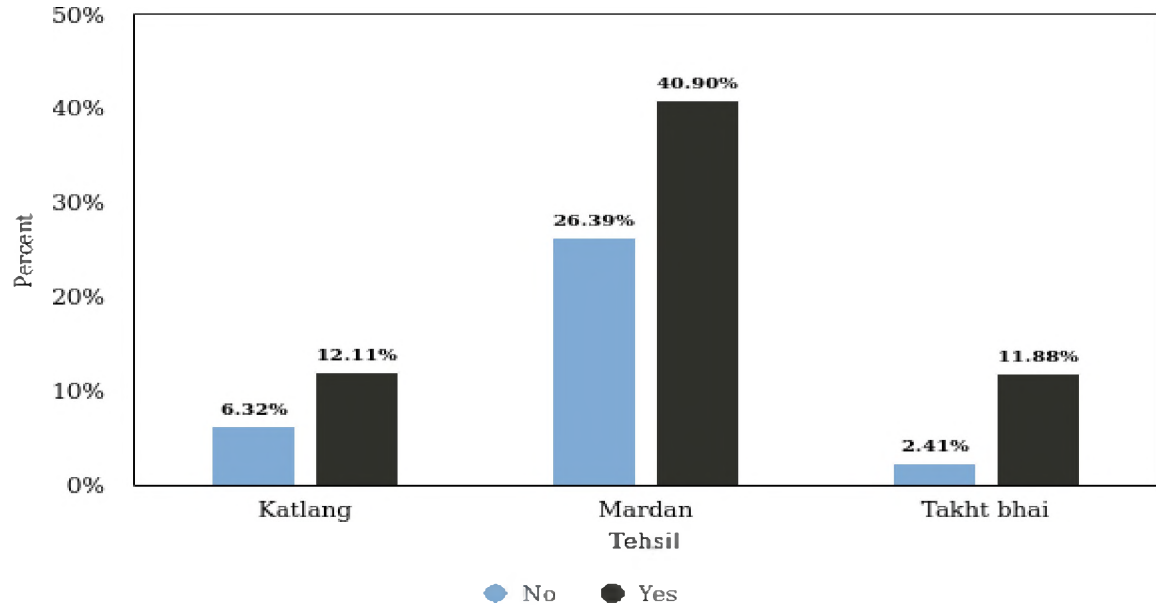


Figure 4. 8: Family Motivation by Tehsil

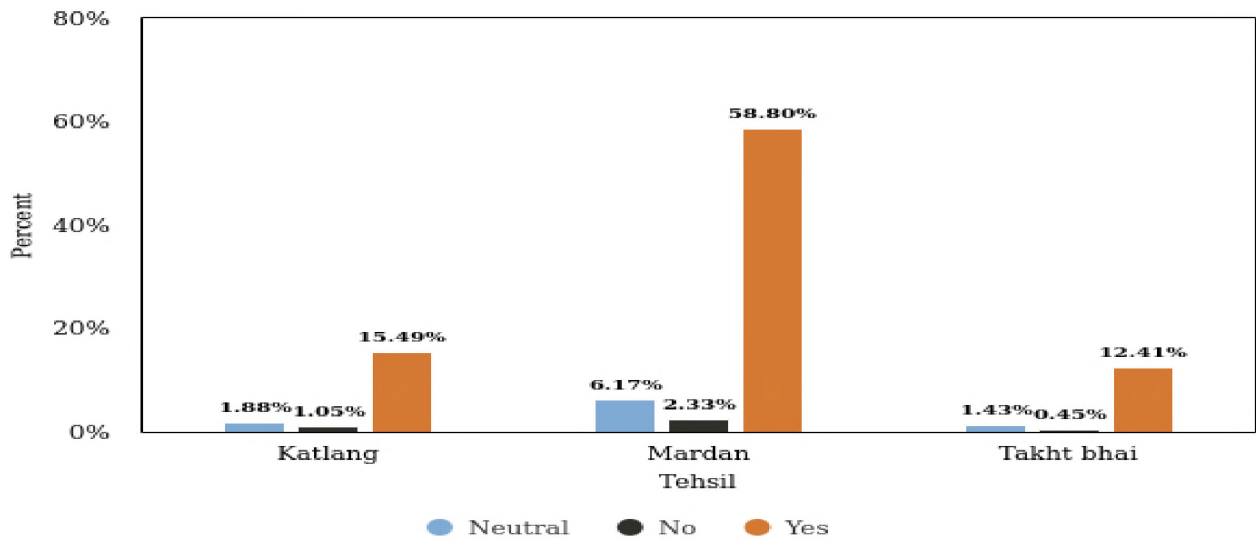


Figure 4. 9: Family Structure Tehsil

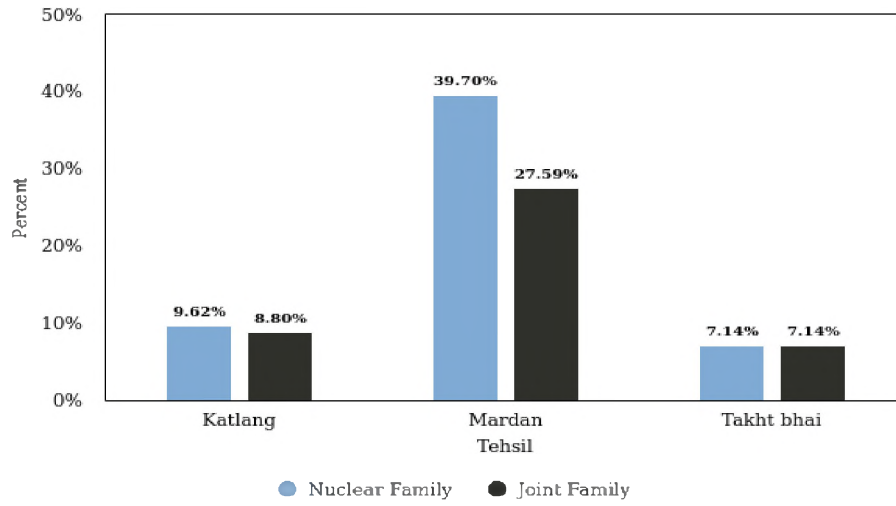


Figure 4. 10: Family Income and Educational Expenditure Distribution (Rs.)

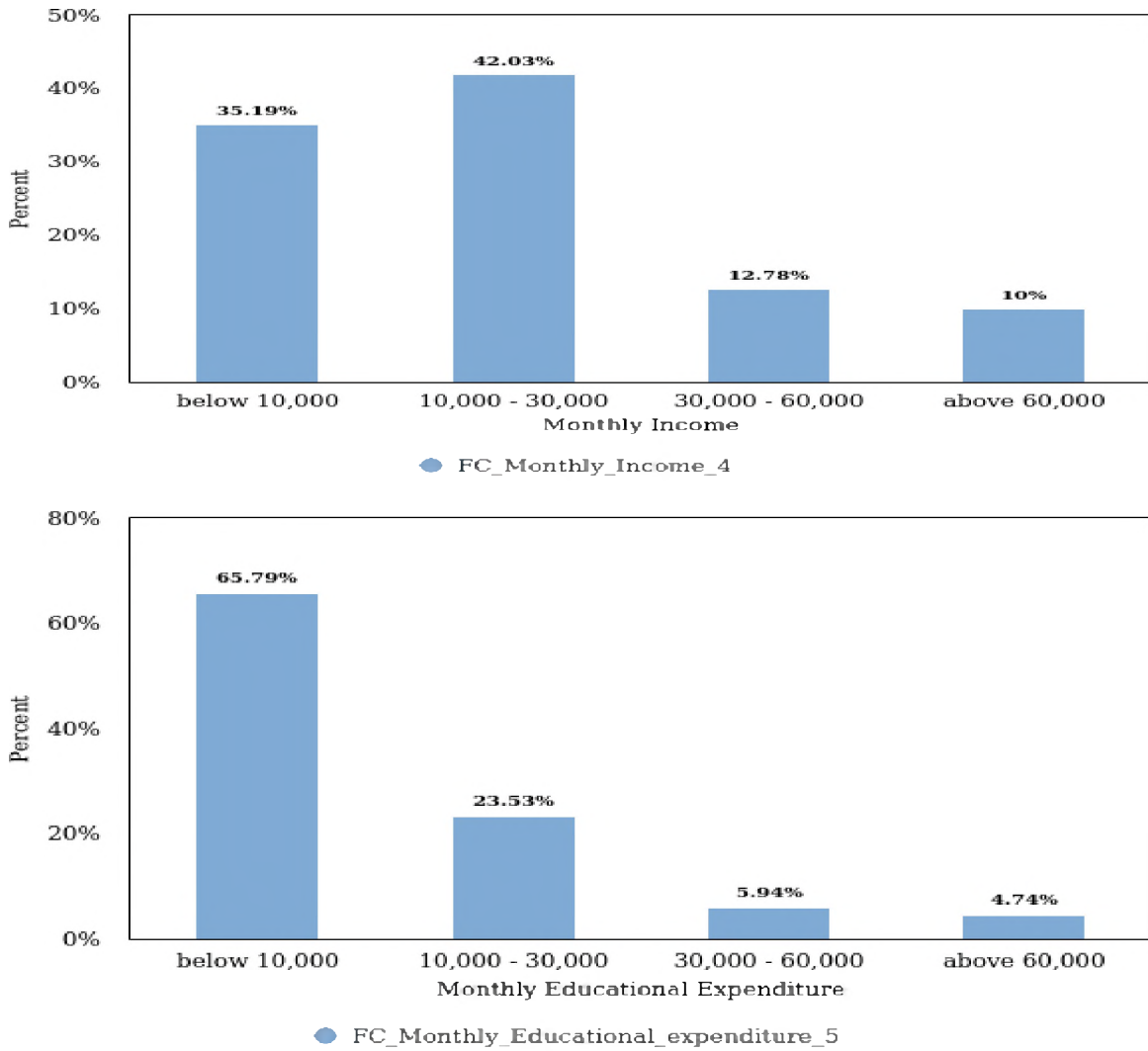


Figure 4. 11: Parents Education Level

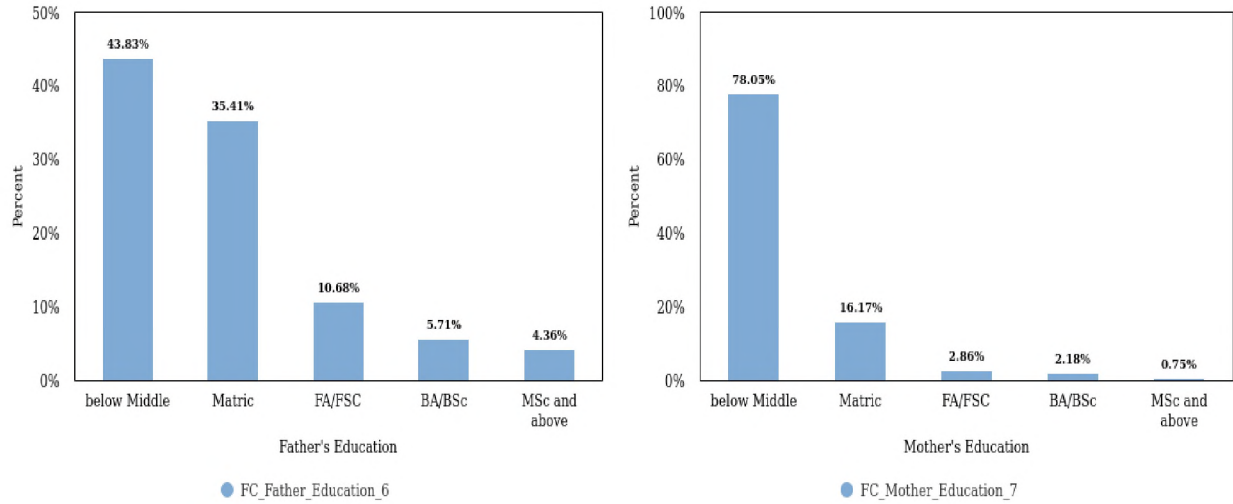


Figure 4. 12: Father's Occupation

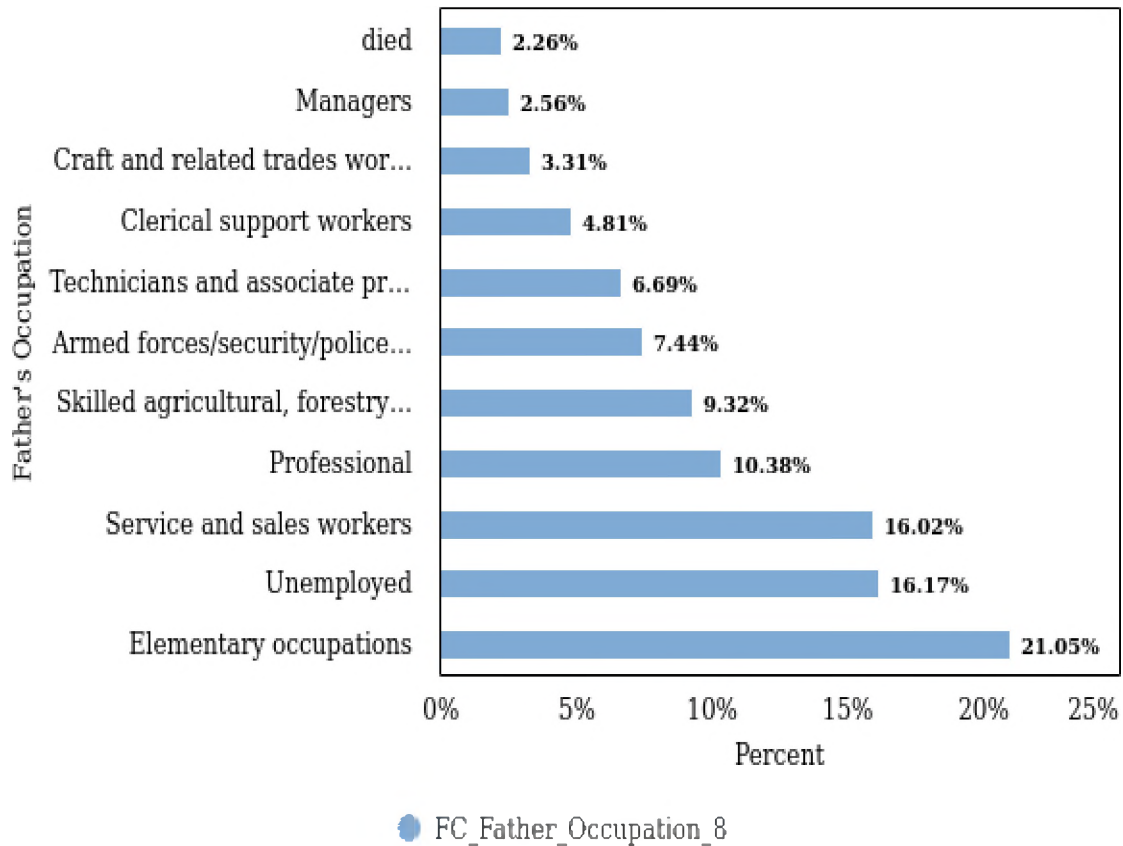


Figure 4. 13: Family values by Tehsil

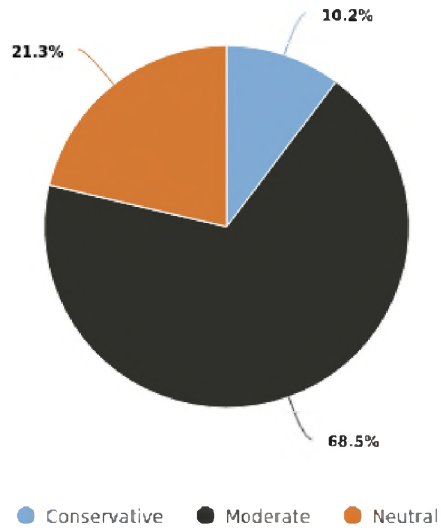


Figure 4. 14: Does your father help in completing the school's task?

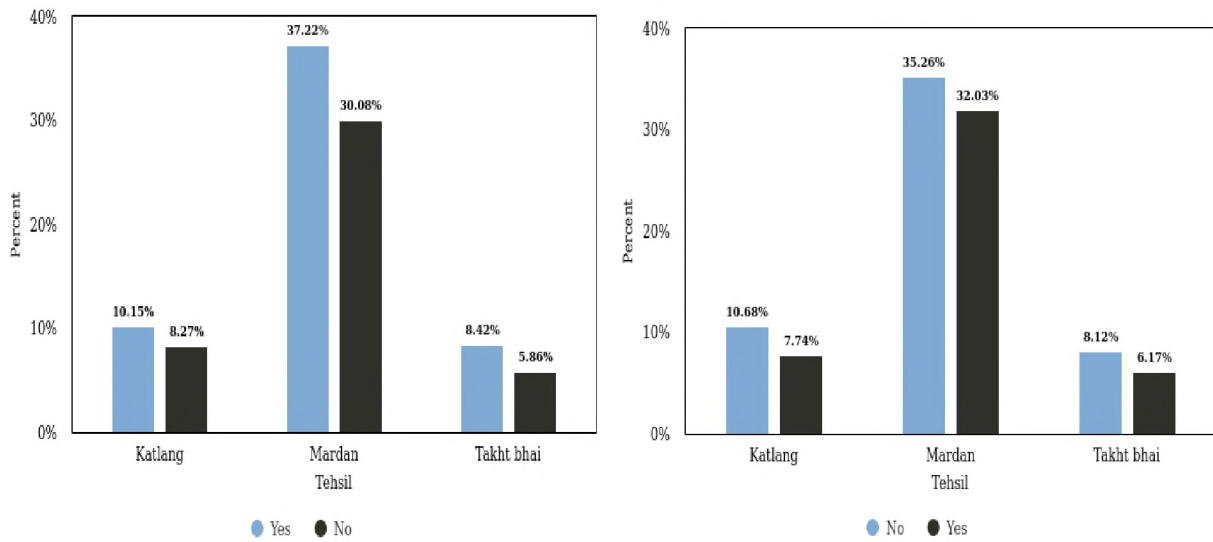


Figure 4. 15: Availability of Internet, library, books at home.

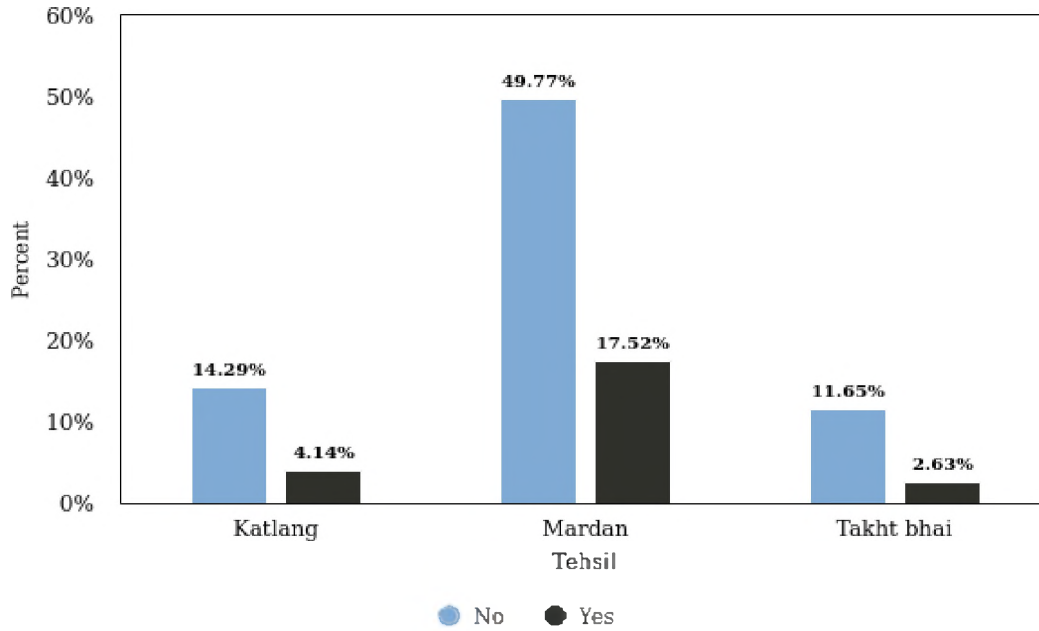


Figure 4. 16: Number of Parents and Teachers Meetings

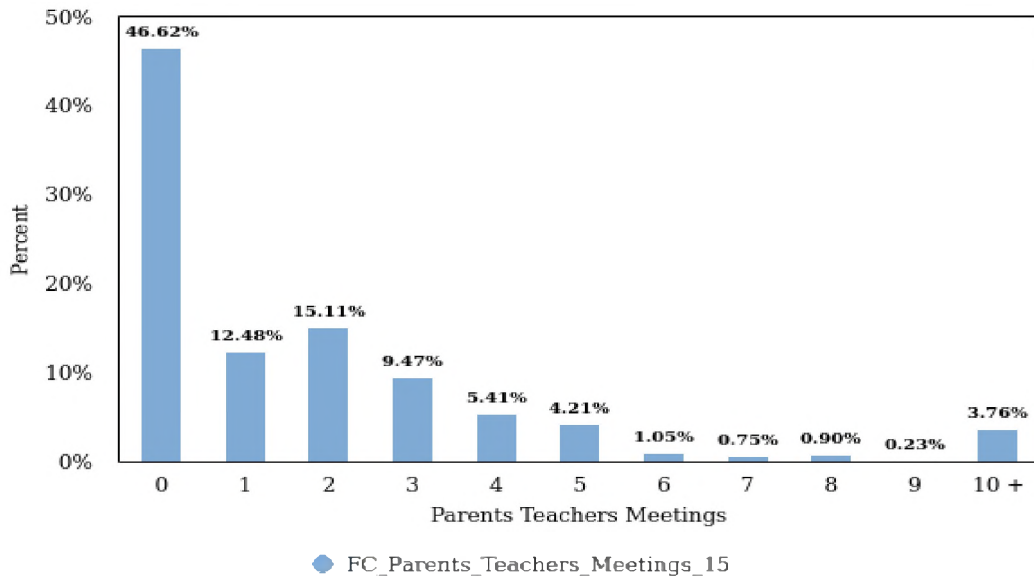
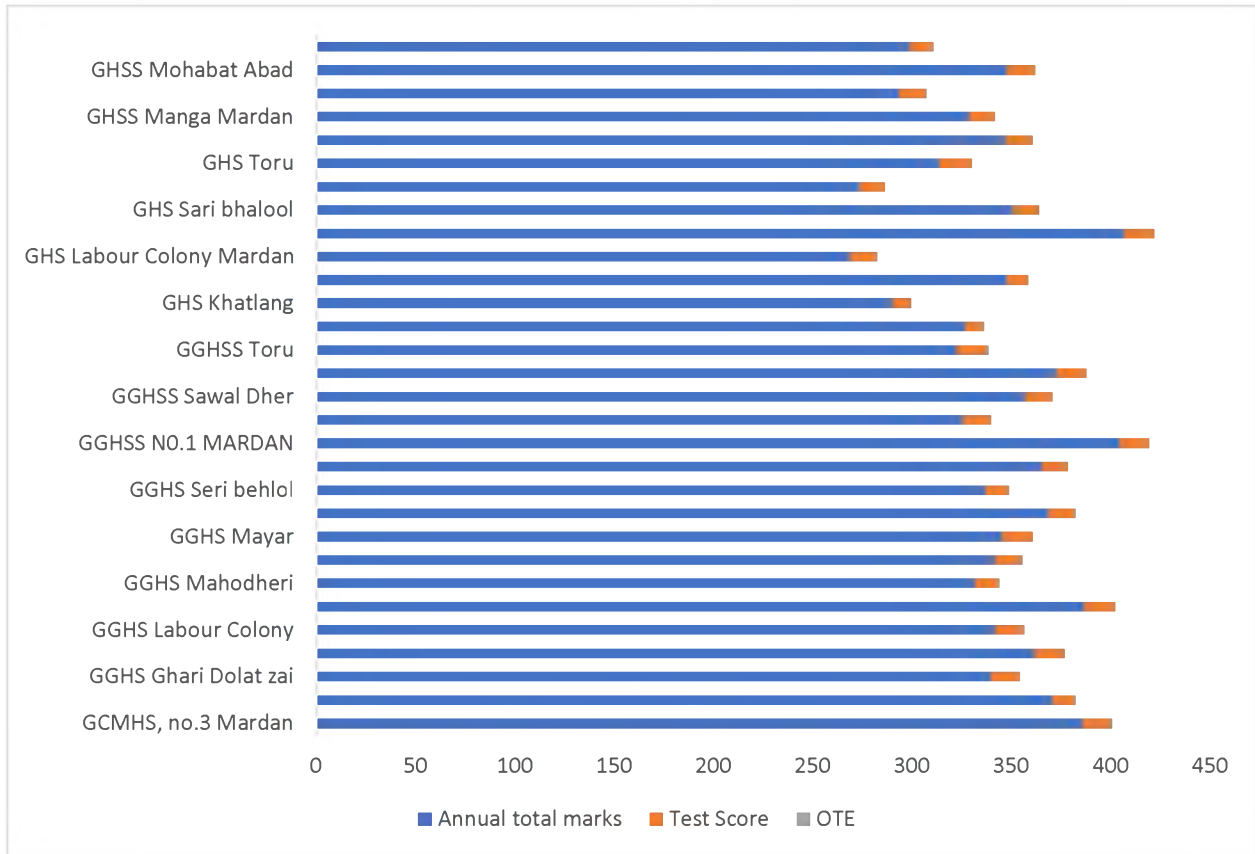


Figure 4. 18: School Mean Performance Indicators.



APPENDIX B

SURVEY QUESTIONNAIRE

Tehsil: _____ Location: _____
City: _____
Institute: _____

A. Individual Characteristics

1. Name: _____ 2. Gender: _____
3. Age: _____ 4. Marital Status: _____
5. Religion: Muslims Christian Hindu Others
6. Ethnicity (Region of Origin) _____
 Urdu Punjabi Sindhi Pushto Balochi Kashmiri
 Balti Hindko Siraki Other _____
7. Total number of brothers and sisters you have. _____
8. Position of Birth: first child middle child last child
9. Any Disability _____
10. Any pressure from family to get position Yes No
11. Do your family motivate you improve your performance. Yes No Neutral
12. Annual percentage in last exam. _____
13. Marks in English, Urdu, mathematics and science, individually.

Subject	Marks	Subject	Marks
English		Urdu	
Mathematics		Science/Biology	
Physics		Chemistry	

B. Abilities

a. Cognitive Abilities

1. Different short mathematical puzzles with increasing difficulty and questions that student might need to solve in their daily routine.

- i. If the price of one dozen eggs is Rs. 144, then what is the price of 1 egg is Rs. _____

A. 11 B. 12 C. 10 D. 8

ii. Mark has a stamp collection. He has 22 stamps from Japan, 34 from Canada, and 17 from Mexico. How many stamps does he have in all?

- A. 53
- B. 63
- C. 73
- D. 83

iii. If $y(x-1)=z$ then $x=$

- A. $y-z$
- B. $z/y + 1$
- C. $y(z-1)$
- D. $z(y-1)$
- E. $1-zy$

iv. Two angles of a triangle measure 15° and 85° . What is the measure for the third angle?

- A. 50°
- B. 55°
- C. 60°
- D. 80°
- E. 90°

v. if price of 1 liter milk is Rs 90, then what is the price of 2.5 liters of milk _____
A. 210 B. 225 C. 180 D. 150

2. English\Urdu reading comprehensive test. This exercise require you to read the text and answer the questions asked.

Obesity is a medical condition in which excess body fat has accumulated to the extent that it may have an adverse effect on health, leading to reduced life expectancy and/or increased health problems. Body mass index (BMI), a measurement which compares weight and height, defines people as overweight (pre-obese) when their BMI is between 25 kg/m² and 30 kg/m², and obese when it is greater than 30 kg/m².

Obesity increases the likelihood of various diseases, particularly heart disease, type 2 diabetes, breathing difficulties during sleep, certain types of cancer, and osteoarthritis. Obesity is most commonly caused by a combination of excessive dietary calories, lack of physical activity, and genetic susceptibility, although a few cases are caused primarily by genes, endocrine disorders, medications or psychiatric illness. Evidence to support the view that some obese people eat little yet gain weight due to a slow metabolism is limited; on average obese people have a greater energy expenditure than their thin counterparts due to the energy required to maintain an increased body mass.

The primary treatment for obesity is dieting and physical exercise. To supplement this, or in case of failure, anti-obesity drugs may be taken to reduce appetite or inhibit fat absorption. In severe cases, surgery is performed or an intragastric balloon is placed to reduce stomach volume and/or bowel length, leading to earlier satiation and reduced ability to absorb nutrients from food.

Obesity is a leading preventable cause of death worldwide, with increasing prevalence in adults and children, and authorities view it as one of the most serious public health problems of the 21st century. Obesity is stigmatized in much of the modern world (particularly in the Western world), though it was widely perceived as a symbol of wealth and fertility at other times in history, and still is in some parts of the world.

Answer the questions below.

- i. The statistics state that.
 - a. although obesity is prevalent, it is not considered as a serious illness.
 - b. obesity is considered as a serious illness.
- ii. Obese people
 - a. may suffer from severe illnesses.
 - b. may suffer from mild ailments.
- iii. Modern medicine
 - a. can cure obesity.
 - b. cannot cure it at all.
- iv. The best treatment for obesity is
 - a. related to individuals lifestyle.
 - b. medical.

3. To measure the analytical reasoning and visual processing differ questions will be asked. Identifying the pattern, selecting the odd object out and others.

For example: What number should come after: 7, 10, 8, 11, 9, 12 ...

- A. 7 **B. 10** C. 12 D. 13

Answer = 10

- i. Look at the pattern below. If the pattern continues, how many dots will be in the next triangle?



- A. 5 B. 10 C. 15 D. 20

- ii. What number should come after: 21, 9, 21, 11, 21, 13, 21 ...
 - A. 14 B. 15 C. 21 D. 23
- iii. What number should come after: 80, 10, 70, 15, 60

A.20 B. 15 C.21 D. 23

For Example: Fill the blank in the series: A, B, D, E, G, H, J, K, ____

A. H B. M C. L D. V

Answer = M

iv. Fill the blank in the series: E, A, ____, O, I

A. E B. U C. X D. V

v. Fill the blank in the series: CMM, ENN, GOO, IPP, _____, MRR

A. ITT B. KQQ C. GRR D. ISS

4. Ability to memories pattern of different objects or number, with increasing difficulty level will be asked to test the short term memory of the student.

b. Non-Cognitive Abilities

On a scale of 1 to 5, with 5 being the highest rating, **please choose the number that best describe your reaction:**

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

1. Self-control: Tangney, Baumeister, Boone, (2014)

Sr. no	Questions	1	2	3	4	5
1	I have hard time breaking bad habits					
2	I get distracted easily.					
3	I finish whatever I start.					
4	I have achieved a goal that took years of work.					
5	New ideas and projects sometime distract me from the previous ones.					
6	I say inappropriate things.					
7	I refuse things that are bad for me, even if they are fun.					
8	I'm good at resisting temptation.					
9	I work hard					
10	People say that I have very strong self-discipline.					
11	Pleasure and fun sometime keep me from getting work done.					

12	I do things that feel good in the moment but regret later on.					
13	Sometime I can't stop myself from doing something, even if I know it is wrong.					
14	I often act without thinking through all the alternatives.					

2. Self-esteem: Negative self-judgments, critical of self

Sr. no	Questions	1	2	3	4	5
1	You feel that you have many good qualities					
2	All in all, you are inclined to feel that you are a failure					
3	On the whole, you are satisfied with yourself					
4	You certainly feel useless at times.					

3. Social Skills: Interpersonal Competence questionnaire (ICQ)

Sr. no	Questions	1	2	3	4	5
1	I love to socialize					
2	I enjoy going to parties and meeting new people					
3	I have lots of friends					
4	I am usually very good at leading group discussions.					
5	I find it very difficult to speak in front of a large group of people.					

Sr. no	Questions	1	2	3	4	5
1	I am very sensitive of criticism.					
2	It is very important that other people like me.					
3	I am generally concerned about the impression I am making on others.					
4	I am often concerned what others are thinking of me.					

Sr. no	Questions	1	2	3	4	5

1	I am a good listener and help my friends in their problems.					
2	I am able to say and do things to support a close companion when he/she is feeling down.					
3	I am able to show genuine empathetic concerns even when the problem is uninteresting to me.					

Sr. no	Questions	1	2	3	4	5
1	I am able to admit that I am wrong when there is a disagreement with a close companion that can end up in a serious fight					
2	I listen to opposite companion seriously and not try to “read” his mind in a fight.					
3	I am good at resolving conflicts.					

C. Effort Level

Sr. no	Questions	No. of Hours/Minutes
1	Number of hours spend in school	
2	Time spent in self-study in week days	
3	Time spent in self-study on weekend	
4	Time spent in self-study during exams	
5	Time spend on getting private tuition	
6	Time spent on traveling to school	
7	Time spent of any paid work	
8	Time spend on household work	
9	How many hours you sleep in a day	
10	Time spend on other actives	

D. Financial Resources

1. School fee _____
2. Educational expenditure on books and copies? _____
3. Expenditure on uniform? _____
4. Monthly Transport expenditure? _____
5. Monthly tuition fee? _____

6. Daily lunch money? _____
7. Do you receive any scholarship from school in the last 12-months? _____
8. Any other expense? _____

E. Family Characteristics

1. Family Structure (joint or Nuclear)
 Joint family system Nuclear
2. Total number of family members _____
3. Number of school/collage/university going children _____
4. Your family's monthly income
 below 10,000 10,000-30000 30000-60000 above 60000
5. Portion of income spent on education of children
 below 10,000 10,000-30000 30000-60000 above 60000
6. Father education
 Below Middle Matric FA/FSc BA/BSc Msc and above
7. Mother Education
 Below Middle Matric FA/FSc BA/BSc Msc and above
8. Father's Occupation
 Managers
 Professional
 Technicians and associate professionals
 Clerical support workers
 Service and sales workers
 Skilled agricultural, forestry and fishery workers
 Craft and related trades workers
 Plant and machine operators, and assemblers
 Elementary occupations
 Armed forces occupations
 Unemployed
9. Mothers' Occupation
 Managers
 Professional
 Technicians and associate professionals
 Clerical support workers
 Service and sales workers
 Skilled agricultural, forestry and fishery workers
 Craft and related trades workers
 Plant and machine operators, and assemblers
 Elementary occupations

- Armed forces occupations
- Home maker

10. Family Values (Conservative/moderate)

- Conservative Moderate Neutral

11. Do your father help you in doing your assignments and homework? Yes

No

12. Do your mother help you in doing your assignments and homework? Yes

No

13. Family member you are close to? _____

14. Availability of internet and Library/books at home Yes No

15. Number of parent and teacher meeting at school in last 12 months. _____