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Does Income Inequality Lead to Educational Inequality? A Cross-Sectional Study of Pakistan

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Abstract

When firms do not know which labor is capable of efficient work, then paying all employees their average product as wage seems a feasible option. This simplest of ways discourages good workers and makes bad workers costly. Spence proposed to use educational attainment as the indicator of the labor force's capability to solve this problem. Since workers are randomly distributed in terms of their ability, Akerlof would lead us to believe that the level of educational attainment should be proportional to the individual's ability, which is not valid, practically. This study strives to find the determinants of educational inequality, where income inequality of the household is the prime suspect, and other indicators include gender, household size, and age. GMM instrumental variable approach was used to study the effect of income inequality on educational inequality. The results showed that it is income inequality, which restricts people from attaining higher education.

Keywords: access to education, income inequality, GMM model, labor force survey

Background

During recruitment, firms face uncertainty in matching the most appropriate labor with the given tasks and in deciding fair wages. At the time of hiring labor for jobs, firms are unaware of the capability of that labor. There is no apparent physical difference between a capable and incapable workforce. Akerlof (1970) proposed that it is nature that defines labor's ability; this process is random and occurs with no physical identification. Spence (1973, 1974) proposed a signaling model to differentiate between high and low capability workers widely used by researchers globally (Arteaga, 2018; Connelly et al., 2011; Chang & Chin, 2018). According to this model, high capability labor is willing to get higher education to prove its capability, thus differentiating itself from the rest of the labor force. Hence, firms can happily pay higher wages to workers who have a higher

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education. Since people are randomly distributed in terms of their ability (Akerlof's analogy), it is expected that labor will be equally distributed in terms of its educational qualification and will earn wages according to its capability (Cole, 2017; Stocké et al., 2019; Stromquist & Monkman, 2014).

Building on Akerlof (1970) and Spence (1973, 1974), educational equality helps firms to efficiently hire new labor and pay wages to workers according to their position in the educational distribution. However, some conditions create hurdles in bringing educational equality (Alfita et al., 2019). These hurdles include an individual laborer's intention to seek a better job, market conditions he is trying to fit in, and resource availability to get higher education (Heckman & Mosso, 2014; Weiss, 2014).

In developing countries like Pakistan, a trained workforce is a significant factor in production, so the proper utilization of its skills is crucial to maximizing the firm's marginal product; this, in turn, can maximize wages (Card et al., 2018). According to Akerlof (1970), there exist some lemons (incapable labor) in the labor market and if we do not filter them through the appropriate selection criteria (interviews, tests or tasks), then anyone can be employed and may expect to get a wage equal to the average produce of labor. This is how a firm tends to pay equally rather than equitably based upon distinguished performances (Stocké et al., 2019; Stromquist & Monkman, 2014). The problem with this average product of labor criterion is that workers who are above average in terms of their ability are discouraged due to average pay, while the remaining labor force, which has working capability lower than the average, is overpaid and becomes a burden for the firm. Hence, the current pay structure leads to the issue of falling productivity, since the majority of highly capable workers either quits or shirks its work and below-average workers enjoy higher than optimal wages. If the firm fires highly capable workers because of their apparent shirking from work or lack of motivation, then the workers left behind would reduce the productivity of the firm (Trpeski et al., 2016; Vinogradova & Grinevich, 2020)

The problem that firms are unable to identify the ability of labor becomes more severe if there is a mismatch between ability and educational attainment. Table 1 shows the level of inequality in education in Pakistan, calculated from the labor force survey data collected for the year 2010. It is observed that 80% of the population gets only half (50%) of the education level required to get employment; looking from an educational attainment point of view, it indicates that almost 80% of the population, has an average or lower ability to work on a job if he or she is hired. Ideally, people should have above average (80%)

educational attainment instead of average (50%). The data also indicated that only 20% of the population is capable enough to access higher educational qualifications. It is further analyzed, if the ability is randomly distributed as mentioned by Akerlof (1970), then the statistics described in Table 1 below ensure that most of the workforce in Pakistan would fail to earn better wages since they do not possess the necessary qualification. The ratio of 80-20 is similar to Pareto's 80-20 rule, whereby 80% of the resources are utilized to complete 20% tasks and 20% resources complete 80% tasks. However, the concern here is that even if Pareto's rule is valid, the 80% would be getting compensation equal to the qualified ones, though they would complete only 20% of tasks.

Using 141283 observations from the Labor Force Survey 2017-18, Figure 1 shows a smooth outward bent curve of educational inequality. It is observed that the increase in educational qualification percentage is gradual for the first half (50%) of the population. It suddenly increases sharply by taking advantage of the Lorenz curve; each percentage of the population is contributing to the total stock of education attained. Furthermore, this curve is comparable across time-wise and region-wise globally. In the figure 1, the 45-degree line shows the ideal case of perfect educational equality; the more the curve bends away from the reference line of 45o, the more it represents the existence of inequality in terms of educational attainment in the Pakistani population.

The gap between the qualification of the randomized population (45-degree line) and unequal educational attainment (curved line) identifies the presence of inequality. This inequality may be associated with some household related social indicators, which restrict individuals from reaching their desired level of educational attainment. While assessing the skewed nature of global income patterns, the most important indicator that leads to educational inequality is the income inequality of the family.

Alvaredo et al. (2018) concluded that the bottom 50% of the population enjoyed only 12% growth from 1980 to 2016, whereas the wealthiest 1% grabbed 27% of resources in these three and a half decades. Income inequality and poverty are used alternatively in economics; the first indicates relative poverty, and the latter indicates absolute poverty (Bonal, 2016). According to the studies by Deyshappria (2018), there are 766.6 million poor people in the world, out of which 50.75% live in Sub-Saharan Africa, and 33.4% live in South Asia. This high incidence of poverty and inequality is expected to hinder access to education and well-being for the households (Ahmed & OlDonoghue, 2010).

Table 1

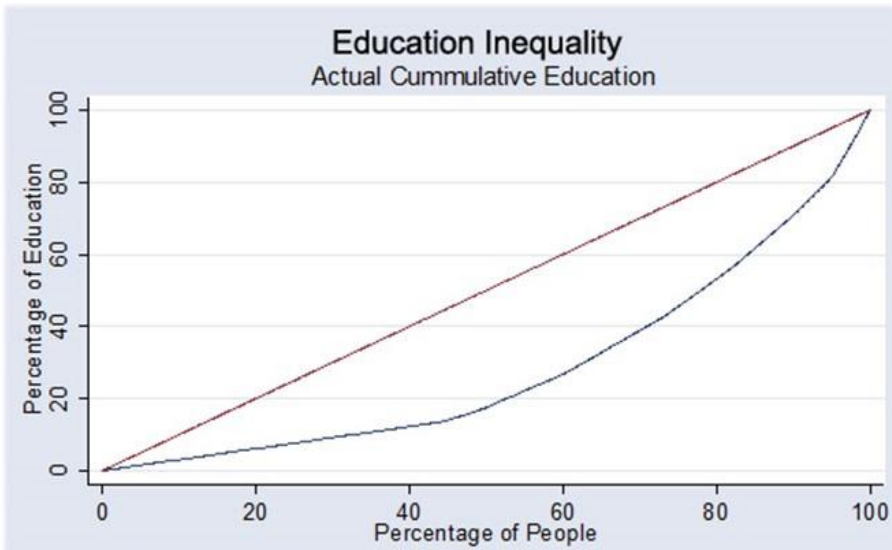
Education Access Inequality

Percentage of Population	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Percentage of Education	3.05%	6.11%	9.17%	12.22%	17.55%	26.72%	38.86%	53.12%	70.84%	100%
Contribution of this 10%	3.05	3.06	3.06	3.05	5.33	9.17	12.14	14.26	17.72	29.16

Note. Source: Calculated from Labor Force Survey of Pakistan 2017-18

Figure 1

Educational Inequality in Pakistan. Source: Self-Calculated Using LFS (2017-18)



Hence, this study was designed to find the indicators, which cause educational inequality in Pakistan. These indicators will then identify how the current screening process of labor proposed by (Spence, 1973; Spence, 1974) is not appropriate for a developing country like Pakistan. The objectives of this cross-sectional study include examining the role of gender, household size, and age of the individual in determining educational inequality. Finally, this study proposes policy prospects to solve this problem.

Literature Review

Empirically, most of the existing research has targeted the effect of education on income level or income inequality. This study transposed 'income inequality' to 'household income inequality' by pooling the income of all the household members, where it is assumed that educational inequality is an individual phenomenon, and the education of an individual depends on the overall socioeconomic conditions of a family. The following studies were used to identify some socioeconomic indicators of households that influence educational inequality.

Many researchers (Cole, 2017; Stocké et al., 2019) have studied the consequences of educational distribution. According to them, higher educational inequality leads to a negative impact on the per capita income of the country because most of the able people get stuck in low paying jobs, which can be discouraging for them. This injustice reduces their faith in the performance to salary link, thus it may possibly lead them to shirk their work.

Some researchers Hertz et al., 2007; Lindahl et al., 2015) proposed that most of the reasons behind educational inequality among individuals are inherited from their parents. They tested the possible determinants based on the survey data of 41 countries and found that differences in the level of parents' schooling affect the differences and the level of schooling of their offspring. It is found that educated parents are benefited by higher income opportunities and are more aware about the returns of education. This knowledge is later transferred to their children pursuing better educational attainment (Maitra & Mani, 2017; Pervaiz & Akram, 2018).

Following Spence (1973, 1974) other researchers (Appelbaum, 2017; Chang, & Chin, 2018; Connelly et al., 2011) also supported the idea of using education as signal of the ability of the worker, as there are psychic costs associated with the attainment of education. According to this theory, individual only attains the level of education where the increased wage matches the increased psychic cost.

Beyond this point, the psychic cost increases exponentially but the wage does not increase at the same rate. This outcome was complemented by others (Bredtmann & Smith, 2018; Savasci, & Tomul, 2013; Stromquist & Monkman, 2014) suggesting that a person gets an education based on its expected payout. There are other factors involved such as gender, average number of siblings and average income to needs ratio of the household; these factors do not increase the expected payout of education but they do influence the psychic cost of education (Bhopal, 2019; Chioda, 2016; Pervaiz & Akram, 2018).

Cortina and Stromquist (2019) based their study on the notion that in third world countries the participation of women in education is lower than that of men, mainly because of the cultural norms which restrict them from attaining higher levels of education and they are also restricted in terms of the fields of study they may choose, especially in the rural areas. Hence, it is expected that women experience a higher level of educational inequality as compared to men (Bhopal, 2019; Cole, 2017; Cortina & Stromquist, 2019). Moreover, Kingdon (2010) presented the case of Uttar Pardesh, India where the difference between the educational attainment of men and women is generated from the difference in intra-household resource allocation for education. In such societies, men are considered bread earners of the family and women have the responsibility of taking care of the household and children.

In accordance with the human capital theory, higher income inequality of the existing household will lead to higher educational inequality of their children in the future; since income inequality reduces access of children to better educational institutes, thus blocking their educational attainment (Psacharopoulos & Yang, 1991; Checchi, 2001; Chang, 2018; Rahman et al., 2018). Therefore, Similarly, Mayer (2001) found that a one standard deviation increase in income inequality led to 10% fall in higher education enrollment in the US. However, researchers (Acemoglu & Pischke, 2000; Rodríguez-Pose, & Tselios, 2011) failed to find any significant evidence of this nature.

Stocké (2007) regarded inequality the main reason of poor educational attainment resulting in the position of the family in lower social class; and he proposed that the number of children in the family and the income of the family act as indicators which determine the decision about their education. The increase in family size increases the financial burden on the household head, who struggles to provide fee and other expenses for children's education (Duncan et al., 2017). It also divides parents' concentration on their children's learning, which reduces their chances to attain a higher level of education in accordance with their abilities. A bigger family size divides the family's lifetime expected income, which reduces the chances of an individual in the family to get an expensive higher education (Ballón et al., 2018).

Jamal and Khan (2005) studied educational inequality in Pakistan and indicated that the disparities in education lead to deterioration in income and poverty distribution, which is the reason the poor are unable to earn the income they deserve in comparison to their inherent ability. Such studies have evidenced the existence of educational inequality and did not find its determinants (Attari et al., 2018; Bashir et al., 2019; Jamal, 2016; Pervaiz & Akram, 2018). Consequent to the effect on income, Filmer and Pritchett (2004) used data from 35 countries including Pakistan and proposed that the major determinant of the differences in educational attainment is the lack of resources and income, which lead to a lack of demand for schooling that was described earlier as low if the parents themselves are uneducated.

Salami et al., (2019) discussed gender differences in access to education in the case of Nigeria. They concluded that females are not given equal opportunities in terms of access to better education. Hence, even though they constitute half of the population, still they do not enjoy an equal access to education.

A similar situation was discussed by (Hall & De Lannoy, 2019) in the case of South Africa. Another study about Ghana by Arkorful et al. (2020) discussed that poverty and education are cyclic, poor families are unable to access higher education which leads to poor job conditions. Only a few studies such as Arshed et al. (2018); Arshed et al. (2019) have explored the role of educational attainment in reducing income inequality in the case of SAARC and Asian economies. According to these studies, the effect of educational attainment is not linear. Hence, there is a need to manage the role of educational attainment so that it is aligned to reduce the income gap.

Checchi (2001) and Jamal and Khan (2005) originally discussed the effect of educational inequality of the individual on his own income inequality and concluded that income inequality of a person may affect his future educational ambitions as well as the overall expenditure required for the educational attainment of his children. Hence, in order to tackle this issue of endogeneity in the cross-sectional data, this study used instruments approach in the GMM framework suggested by Baum et al. (2011), which breaks the flow and effect of educational inequality on income inequality in order to find consistent estimates. Secondly, this study used family income inequality instead of individual income inequality, which is only a small portion of family income inequality.

According to (Baum et al., 2011), the objectives included in the instrument must split the variables into two parts, the first is independent of the dependent variable and the second is a random component. Once this is done, the independent part is used as the instrumented variable. In this way, the endogeneity of the series is broken[1]. There are three further tests labeled as under-identification of instrument test[2], weak identification of instrument test[3] and over-identification of instrument test[4], respectively. Once all the tests are cleared, then the estimated results of the effect of income inequality on educational inequality become consistent.

This study proposes some indicators of individuals and household which are expected to remain unaffected by educational inequality but they are correlated with and explain income inequality, such that their inclusion as instruments removes the effect of educational inequality on income inequality. These instruments include the willingness of the individual to remain available for more work, recent migration from one district to another, and co-effect of doing more than one job. These instruments theoretically explain the existence of income inequality of the family and individual. However, they do not significantly explain educational inequality.

There is no empirical research work available which evaluates the effect of income inequality of the family on the educational inequality of the members of that family through the use of instrumental variable technique in the Pakistani context. The use of this technique can exclude the reverse effects as per human capital theory of positive relationship of educational attainment with income level.

[1]This is checked through endogeneity test provided by the GMM model. If there is endogeneity then independent variable cannot be used.
[2]This test checks whether the reverse connection of dependent variable with independent variable still exists or not. If it exists, then it means that the included instruments do not fully identify the model.
[3]This test checks the correlation between instruments and independent variable which is to be instrumented. In order to solve the issue of endogeneity, instruments should be highly correlated with the independent variable.
[4]For removal of endogeneity, the proposed instruments must not correlate with the residuals of the model because if it is true, then they will correlate with the dependent variable.

Methodology

Educational and Income Inequality Variables

Educational and income inequality are calculated based on the individual's level of education and his / her family's total income, respectively. The procedure is illustrated below.

The indicator of income inequality is constructed by calculating the share of income of each individual of the household, which is computed by dividing the total household income with household size. This study hypothesizes that a household distributes an equal share of its pooled income to each one of its members. This income data is arranged into an ascending order to calculate the cumulative income. Then, it is converted into a 0-100 index scale by subtracting the lowest value from the total, dividing it by the maximum value of data and multiplying it by 100. Thus, generated value represents income inequality and in order to see its intensity, we need to calculate the hypothetical income equality line. This 45-degree reference line is drawn by dividing the highest number, which is 100 into 141283 equal parts, one for each respondent in the sample. Then, the cumulative variable is calculated. If these two variables are plotted, the graph shows that the income data is bent downward away from 45-degree reference line showing the existence of income inequality.

A similar method is used to estimate educational inequality. However, in this case, this study did not pool the educational level of the household as an individual cannot pass on his / her qualification to another.

Model

Based on literature review, the following is the stochastic form of the cross-sectional model used in the estimation process.

$$\mathbf{EDINC_i = \alpha_0 + \alpha_1\, ININC_i + \alpha_2\, HSIZE_i + \alpha_3\, AGE_i + \alpha_4\, GENDER_i + \mu_i} \qquad \textbf{(1)}$$

Here,

EDINC = Educational inequality

ININC = Income inequality

HSIZE = Household size

AGE = Age of the individual

GENDER = Gender of the individual

Since it is suspected that both income inequality and educational inequality affect each other, problem of endogeneity in this model is represented in the equation as follows:

$$\mu_i = f(ININC_i)$$

Statistically, this endogeneity is very hard to detect. One method of checking it is the Hausman Test in which two models are prepared in such a way that two variables which affect each other are used once each as the dependent variable.[5]

$$EDINC_i = f(ININC_i, Controls) + \varepsilon \quad \text{----- Model A}$$
$$ININC_i = f(EDINC_i, Controls) + \nu \quad \text{----- Model B}$$

Now, let us check the presence of the reverse relationship in the model using the residuals from model A against income inequality and the residuals of model B against educational inequality.

$$ININC_i = \beta_0 + \beta_1 \varepsilon + u$$
$$EDINC_i = \theta_0 + \theta_1 \nu + w$$

Here, if β_1 is significant then it means that model A is inconsistent because the dependent variable is affecting the independent variable. Similarly, if θ_1 is significant then model B is inconsistent. Hence, Table 2 shows that both models A and B are appropriate in the case of Pakistan, such that income inequality is causing educational inequality and vice versa. In this situation, if only model A is estimated then it is invalid because it is tantamount to assuming that model B does not exist. This assumption will lead to the issue of endogeneity and contemporaneous correlation which is confirmed by insignificant coefficients and the significant value of correlation, respectively.

Table 2

Hausman Test

Test	Coefficient	t value (Probability)
Dependent = EDINC Independent = Residuals of Model A	-4.69×10^{-11}	-0.00 (1.00)
Dependent = ININC Independent = Residuals of Model B	-1.00×10^{-11}	-0.00 (1.00)
Correlation Between Residuals of Models A & B	-0.0375 (0.00)	

[5]The inference of this test does not vary with the use of controls if they are not affecting the independent variable

In the presence of contemporaneous correlation, this model has to be estimated using the Seemingly Unrelated Regression Estimates (SURE) or the Simultaneous Equation Method (SEM), which will estimate these two related equations simultaneously. This study used the GMM approach and instruments to counter endogeneity as the objective of the study is to evaluate the effect of income inequality on educational inequality as shown in equation (1) (Baum et. al 2011). This study used the GMM approach instead of 2SLS IV regression because GMM provides more efficient estimates as compared to its OLS counterpart and the post-estimation tests provided by GMM are helpful in determining the reliability of the model.

Hence, we have the following model to determine educational inequality.

$$\mathbf{EDINC_i = \alpha_0 + \alpha_1\, ININC_i + \alpha_2\, HSIZE_i + \alpha_3\, AGE_i + \alpha_4\, GENDER_i + \mu_i} \quad \mathbf{(2)}$$

Since it has been proved that educational inequality and income inequality are causing each other, this two-way relation creates endogeneity which is represented in terms of significant correlation between income inequality and the residuals.

$$\mathbf{E(ININC_i, \mu_i) \neq 0}$$

This problem necessitates that we should employ some instrumental variables, which help in breaking the correlation between income inequality and the residuals. The background regression equation which is estimated to split the variable of income inequality is shown below as equation 5.

$$\mathbf{ININC_i = \beta_0 + \beta_1\, AW + \beta_2\, MIG + \beta_3\, AW{*}MIG + \beta_4\, AW{*}GEN + \beta_5\, TO{*}GEN + \varepsilon_i} \quad \mathbf{(3)}$$

$$\mathbf{E(Estimated(ININC_i)\, ,\, \mu_i) = 0}$$

Here,

MIG = recent migration from one district to another
AW = individual available for more work
TO = individual employed in more than one occupation

The following is the final estimation model and its validity depends on the post-regression diagnostics mentioned earlier. Here, instead of income inequality we used the estimated value of income equality generated by equation 5.

$$\mathbf{EDINC_i = \alpha_0 + \alpha_1\, Est(ININC)_i + \alpha_2\, HSIZE_i + \alpha_3\, AGE_i + \alpha_4\, GENDER_i + \mu_i}$$

Table 3

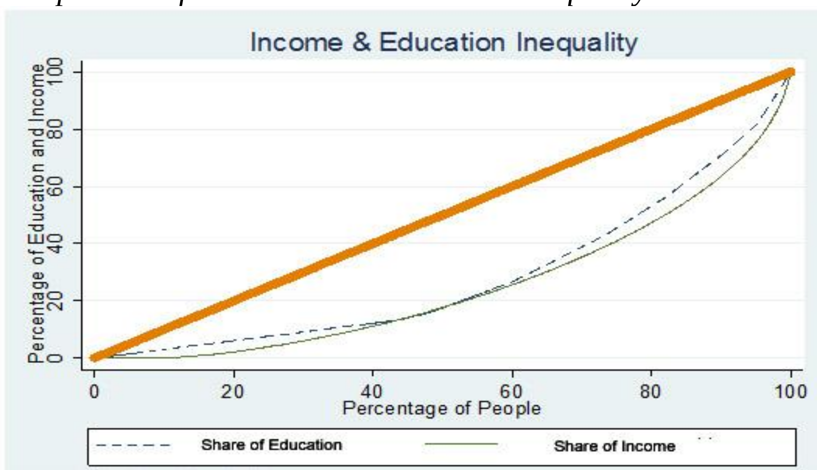
Income and Educational Inequality

Percentage of Population	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Percentage of Income	0.05%	2.19%	6.03%	11.18%	17.68%	25.62%	35.30%	47.31%	63.49%	100%
Contribution of this 10%	0.05	2.14	3.84	5.15	6.50	7.94	9.68	12.01	16.18	36.51
Percentage of Education	3.05%	6.11%	9.17%	12.22%	17.55%	26.72%	38.86%	53.12%	70.84%	100%
Contribution of this 10%	3.05	3.06	3.06	3.05	5.33	9.17	12.14	14.26	17.72	29.16

Note. Source: Calculated from Labor force Survey of Pakistan 2017-18

Figure 2

Comparison of Income and Educational Inequality in Pakistan



While comparing the Lorenz curves of income and educational inequality, it is demonstrated that educational inequality is a bit smaller than income inequality in the case of Pakistan; it means that the share of education is higher than income while contributing to inequality. According to the percentile wise breakup of the total sample shown in Table 3, 50% population holds almost an equal share of education and income, which is 17%. However, inequality is distributed differently beyond this point; inequality lowers when 80% of the population gets to half (50%) of the desired educational attainment. The final 10% population holds 36.51% share of income in the sample, whereas they only hold 29.16% share of educational attainment stock.

Control Variables

The dependent variable of the study is educational inequality; hence the control variables conforming to previous empirical studies are natural algorithms of household size, age, and gender of the individuals. The signs of correlations shown in Table 4 are expected to confirm the literature review; a bigger household size puts pressure on income resources available to fulfill the educational requirements of every member. Moreover, in the case of Pakistan, it is not women who receive low education; instead, male students are withdrawn from education at an early stage for the sake of job if the family is facing financial constraints. Finally, the impact of age on inequality is negative, as older people tend to gather resources to get higher education.

Table 4

Correlations of Control Variables

	Correlation	Probability
Log of Household Size	0.03	0.00
Log of Age	-0.08	0.00
Gender	0.09	0.00

Instruments

Since reverse effect/endogeneity exists due to educational inequality to income inequality as per human capital theory, so there is a need for instrumental variables that are highly correlated with income inequality and not correlated with educational inequality to sort the endogeneity problem. Similarly, these instruments have to pass the under-identification, weak identification, and over-identification tests in order to ensure that the results generated are consistent.

Table 5

Correlations of Instrumental Variables

	Correlation with Income inequality	Correlation with Education Inequality
Looking for more work	0.005 (0.31)	0.01 (0.00)
Recently migrated	-0.05 (0.00)	-0.07 (0.00)
Looking for work and migrated	0.01 (0.12)	0.01 (0.20)
Looking for work and male	0.01 (0.01)	0.03 (0.00)
Having more than one occupation and male	0.01 (0.03)	-0.001 (0.21)

Estimation

In Table 6 are given the estimates of the GMM model calculated for the determination of educational inequality. Some diagnostic tests were provided to ensure the suitability of instruments used and the proper exclusion of any sort of endogeneity present in the model. In this model, since there are five instruments provided for one endogenous variable, as shown in equation 3, hence there is a need to check if we have over-identified the endogenous variable (income inequality). The Sargan J over-identification test, which yielded insignificant results, as shown in Table 6, suggests that the instruments used did not over-identify income inequality.

Since the purpose of the variable was to ensure the splitting of the endogenous variable (income inequality) in such a way that only the exogenous portion is included in the model, Kleibergn-Paap LM test was used to confirm whether instruments were underperforming or not. The significance of this under-identification test indicates that the instruments have been successful in realizing their objective. Another objective of instruments was that exogenous variables must be strongly correlated with the endogenous variable and. The results indicate that the proposed indicators are strongly correlated with variable income inequality. Finally, the endogeneity test checked the correlation of the endogenous variable (income inequality) with the residuals, and its presence indicates the presence of endogeneity. The result of this test is insignificant, showing the absences of endogeneity in the model after the instrumentation of income inequality, hence no need to introduce new instrument. Finally, since the GMM model is sensitive to heteroskedasticity, GMM robust was used to ensure that the estimates were reliable even in heteroskedasticity. Hence, it is validated that the proposed instruments are accurately identified, able to break the endogeneity between educational inequality and income inequality, thus making this model consistent. The use of 38424 valid observations in the estimation of educational inequality leads to a significant model. The significant values of the F test and high R square represent that the proposed variables are 80% successful in explaining the variations in educational inequality. Indeed, these values represent the comprehension of the model, considering the data to be cross-sectional and behavioral.

According to the estimates, if income inequality of the individual increases by 1%, on average, it leads to a 0.24% increase in educational inequality. The result indicated that a deprived household must get compensated with immediate or future educational expenditures.

Regarding the increasing burden of the dependents, if the household size increases by 1%, it increases educational inequality by 0.91%, on average. These results are plausible, considering household earners have to decide between current expenditure and investment in educational attainment, which might increase the income of their offspring. Hence, if there are more dependents in the household, it leads to lower per person funds available for education. These results are further supported by Stocké (2007).

The age factor shows the time taken by the individuals in saving resources for educational purposes. In this model, an increase of 1% in the age leads to a 3.75% fall in education inequality among individuals. Therefore, itis safely inferred that in Pakistan, people might raise their educational attainment levels steadily, giving the idea that educational inequality dissipates over a certain time. Nevertheless, this cannot be rendered good news because of the increase in age lessens job life.

This model concludes the debate on who is most affected by educational inequality. Cortina & Stromquist (2019) insisted that females are discouraged from getting an education based on cultural norms, whereas, Psacharopoulos and Yang (1991) opined that male students end up being first to drop out of school at an early age for the sake of job in case of any income constraint. The estimation results revealed that in male students, inequality increased by 3.87%, on average. Hence, the results support the proposition by Psacharopoulos and Yang (1991) for Pakistan.

Table 6

Determinants of Educational Inequality

Variables	Coefficients	t values (Probability)
Income Inequality	0.247	2.08 (0.03)
Log Household size	0.912	6.94 (0.00)
Log of Age	-3.750	-29.3 (0.00)
Gender	3.870	14.2 (0.00)
Constant	21.30	6.61 (0.00)
Diagnostics		
R – Squared	0.81	
F test	542.6	0.00
Under Identification Test		
Kleibergn-Paap rk LM Statistic	83.37	0.00
IV redundancy test	81.63	0.00
Weak Identification Test		
Kleibergen-Paap rk Wald F-Stat.	16.92	
Stock-Yogo Weak Identification Critical values 5% maximal IV: 14.37		
Over-Identification Test		
Hansen J Statistic	5.54	0.24
Endogeneity Test	1.38	0.24

Conclusion and Policy Implication

Based on Akerlof (1970) and Spence (1973, 1974), it is clear that the principal criterion of firms for recruiting labor is the educational qualification. It represents the length to which the high ability person has gone to prove his ability. However, if the analogy of random distribution of labor concerning ability proposed by Akerlof (1970) is right, then there must not be inequality of education (Card et al., 2018).

It is further established when the Lorenz curve is constructed, the increase in population should match the increase in educational attainment achieved in a particular population (Weiss, 2014; Lee & Lee, 2018). This philosophical analogy was met with criticism in this study. Based on the data of Labor Force Survey 2010, there is ample evidence that inequality in educational attainment exists among the populace. Empirical evidence suggests that there might be some structural factors at play in the household and economy that restrict individuals to attain a high educational level, thus deviating from the ideal situation of educational equality. Hence, if firms only use educational attainment as an indicator of ability, this would lead to injustice with some potential and able workers (Erikson, 2016).

This inequality generally has some harmful effects, one of them is people not getting equal opportunities to receive better education, which deprives them of a chance to secure better jobs and higher income for their family in future (Heckman & Mosso, 2014; Lindahlet et al., 2015). Such inequality provides unjust outcomes for the individual who is unable to attain the level of education that he should because of economic constraints. Consequently, this may encourage the individual to shirk his work or resort to illegal ways to meet his/her expenses. Hence, this study was built on the strong argument to find the possible social indicators, which are determinants of the education attainment deprivation, in order to provide evidence that education is not a complete indicator of individual ability (McCartney et al., 2017).

This study proposed indicators such as the size of the household, age of the individual, gender of the individual, and income inequality in the family as possible determinants of educational inequality (Bredtmann & Smith, 2018). Since educational inequality may also lead to income inequality of the individual, this study used an instrumental GMM model to counter the endogeneity problem. Careful estimation of GMM model ensured the alleviation of endogeneity by using instruments that led to consistent results (Ullah et al., 2018; Ullah et al., 2020). These results showed that other than age, which negatively affects educational inequality, all other indicators positively affect educational inequality. Therefore, it is concluded the bigger family size; the larger would be the income inequality level blocking the capable workers to acquire the desired level of education that would have helped them to enter the higher income group matching with their abilities. Otherwise, starting with a meager salary, a long time would be required to prove their ability, resulting in a satisfice. The structural variables proposed are not in the control of the individuals, hence this study invites the government to intervene and help in opening up the bottlenecks.

The positive impact of gender showed that in Pakistan, it is the male student who is withdrawn from education if the family is facing financial issues. Male students are the first to sacrifice their education to participate in the family income-earning process, as is the case in developing countries of Africa (Ballón et al., 2018). In this regard, the government can help the students enroll in public and private schools by introducing financial aid to reduce dropouts. Educational institutes can offer evening and weekend educational programs at school level as well in order to increase primary and secondary school enrollment (Arshed et al., 2019; Rahman et al., 2018).

Social security and support can be provided to large families to invest in their offspring's future. Financial institutions such as banks and insurance companies can provide long-term risk-free savings, which may enable parents to pursue higher education. Higher Education Commission (HEC) of Pakistan needs to increase the number of local and foreign scholarships given to students so that more and more people can avail low cost higher education and get out of the trap of income inequality (Qazi et al., 2018; Salik & Zhiyong, 2014).

The income inequality of the family leads to failure in attaining higher education by their children, so any means employed to reduce inequality or to ease educational attainment by the government will lead to lower inequality in education (Bredtmann & Smith, 2018; Chioda, 2016). The government must promote child education insurance or provide additional support to low-income households to manage their expenditures, helping them to self-sustain as better qualified youth will be raised, leading to higher household incomes (Arteaga, 2018; Khalid, 2018; Lindahl et al., 2015).

The advantage of the two-way relation of income inequality and educational inequality is that any intervention that leads to lower educational inequality today ensures lower income inequality in the future, which in turn lowers the considerable pressure of educational inequality (Alfita et al., 2019; Stocké et al., 2019).

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