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Distributional Inequalities Up Against Income and Consumption

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Abstract

This research delves into the important issue of economic inequalities highlighting its importance from a humanitarian standpoint as well as for inclusive growth which is crucial for achieving sustainability. Focusing on Pakistan, it analyses factors influencing the distribution of income and consumption nationally as well as provincially using data from the Household Integrated Economic Survey (HIES). Employing the Conditional as well as Unconditional Quantile Regressions method, this study evaluates the impact of various determinants on all sections of the earnings distribution. The finding underscores the multifaceted nature of distributional inequalities, influenced by various endogenous as well as exogenous factors including individual characteristics and labour market characteristics.

Keywords: Income Inequality, Consumption Inequality, Re-centered Influence Functions (RIF), Quantile Regression

JEL Codes: D31, D30, R12, C10

Introduction

The increase in income inequality in the last few decades is a well-documented fact in Pakistan. Many empirical studies related to Pakistan have concluded a strong upward trend in income disparities among household income. Continual disparities hamper growth, encumber poverty reduction, arouse social disparity and thus fuel crimes. Thus, the most critical challenge of this century is to evade this inequality trap. The interest of the economists in combatting this challenge can be attributed to Global Goals 1 and 10, which seek to eradicate poverty for all people ubiquitously and lessen inter and intra-country inequalities. These disparities are traceable to increases in the dispersion of the permanent element of income as well as to an increase in the volatility of the transitory element of income. However, from the viewpoint of welfare only focusing on changes in current income might not be a sufficient indicator. The lifetime resources available to households may not be fully reflected by the level of current income. As per the life cycle hypothesis income increases in working age and then declines, because of this observant fact individuals save in their working age to smooth their consumption in due course (Modigliani 1954; Friedman 1957). Individual's consumption patterns may differ from income patterns in the case of borrowing and saving or if they receive income from any other sources like social securities' provided by the government. The social securities may append the ability of individuals to consume particularly for the lowest quintile of income in contrast to the upper quintile. If the lifetime hypothesis becomes significantly true in reality then it might have many policy concerns, e.g. current income is not enough to measure inequalities. As reflected in the graph the inequalities of income in Pakistan are higher than consumption for all provinces as well as at the regional level.

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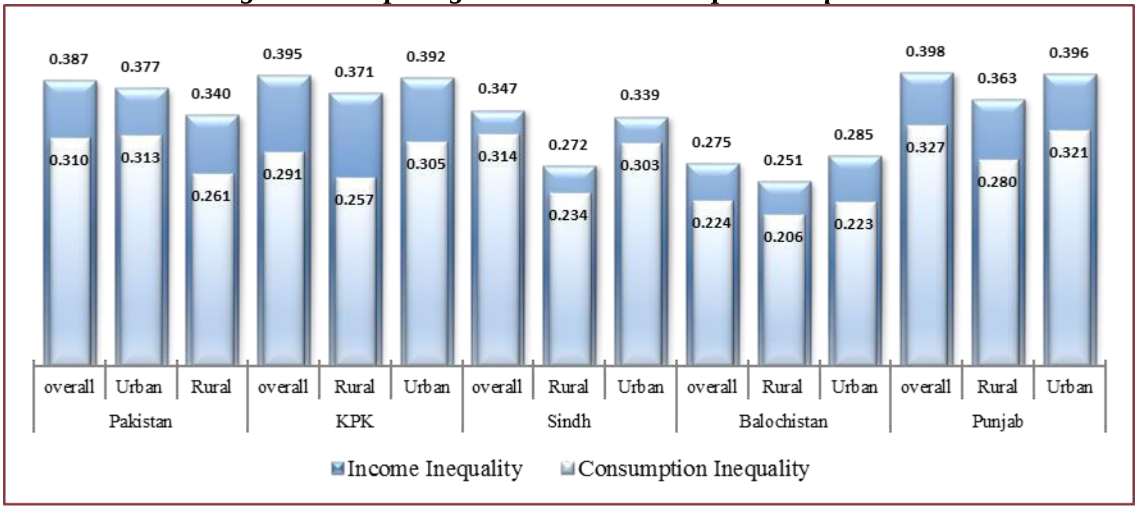
Figure-1 Comparing income and consumption inequalities.



Source: Author estimation using HIES, 2018-19

Therefore, the joint analysis of income and consumption inequalities might be enlightening in several aspects. It can shed light on the mechanism of smoothing consumption and help to measure the well-being of individuals as well as the distribution of resources. The goal of this study is to give insight into the variables that determine the distribution of income and consumption. It seeks to explore aspects such as the influence of the educational profile of the labour force on the distribution of earnings, the significance of asset composition in the distribution of income and consumption, and the role of high-paid and low-paid occupations in determining the distribution of labour earnings. The analysis is done at the national level as well as for provinces using data from the household survey. The empirical assessment mainly makes use of the unconditional quantile regression method, proposed by Firpo et al. (2007). This method estimates the influence of possible determinants on all sections of the earnings distribution, making it better suited to answering concerns regarding the causes of earnings inequality for different segments of distribution than traditional least squares techniques, which only estimate effects on mean income or consumption. Moreover, the analysis is supplemented by Conditional quantile regressions (Koenker & Basset 1978). This technique has been widely used in empirical applications – in contrast to the more recent unconditional quantile regression technique – it does not allow for conclusions about the impact of a variable on overall earnings inequality but rather provides information about the distribution of earnings within different subgroups of the population. This study supplements existing empirical literature on household inequality in various ways. First, it deepens the existing national literature in terms of providing comprehensive and essential knowledge on understanding the inequality patterns prevailing in the economy that help decision-makers in formulating appropriate policies intended to reduce inequality at both household and regional levels. Moreover, it is the first study in the context of Pakistan that provides the comparative assessment of contributing factors of income and consumption inequality using both conditional and unconditional quantile regression.

The rest of the paper is organized into the following sub-sections: Section Two scrutinizes the existing empirical literature regarding both income and consumption inequality, Section Three discusses a framework for the study, Section Four sheds light on the estimation technique and data employed, Section Five discusses the results and final section concludes.

Review of Literature

The empirical research that focuses both on income and consumption to measure inequalities gives somewhat mixed results. Stiglitz et al (2009) emphasized the joint consideration of income, consumption and wealth to measure the distribution of material well-being of individuals because studying these separately may be responsible for missing the essential connections between them. Recent evidences give an idea about these connections that the levels of income, consumption and wealth inequalities are dissimilar with each other. Some of the studies concluded that consumption inequalities have risen not as much of the inequalities in the distribution of income (Cutler & Katz 1991; Heathcote et al.; 2010, Fisher et al.; 2013; Meyer & Sullivan 2013). Others concluded that there is not such a significant difference in the distribution of income and consumption therefore both give rather similar results (Aguiar & Bils 2015; Attanasio et al. 2014). Fisher et al (2015) demonstrate that the average propensity to consume diminishes with income and is usually very high for the lower-income group. In contrast, wealth increases as income increases and gives a higher wealth-to-income ratio for the upper-income group. Consequently, inequalities in consumption remain less than income and further inequalities in income remain less than wealth inequalities. Also, the measurement of inequalities using income only might not reflect the actual depiction of how the living standard of a household is disseminated. As the underreporting of income might lead to underestimations of inequalities. Therefore, the distribution of consumption might provide a good comparative measure of inequality among households. Therefore, it is worthwhile to track the material well-being of individuals by considering more than one measure. Recently, this argument has been brought to the forefront of the microeconomic literature on inequality. There is much desideratum not only to shed more light on the existing contradiction-prone evidence but also to examine the influential factors that are responsible for income or consumption inequalities, more rigorously from Pakistan's perspective.

Numeral empirical studies have endeavoured to elucidate inequalities from various standpoints. Inequalities are considered a multidimensional complex phenomenon therefore various theoretical perspectives have been developed about the potential determinants of the distribution of income and consumption of households at both macro and micro level. The studies that are mainly based on time series data are mainly focused on macroeconomic determinants of inequality such as inflation and unemployment (Mocan 1999; Blejer & Guererro 1990), whereas some other time series studies investigate the ramifications of fiscal policy on inequality (Auten & Carroll 1999; Feenberg & Poterba, 1993). Moreover, several studies have tried to study the macroeconomic determinants of inequality in a broad spectrum within a multi-country setting. Such determinants are a combination of the aforesaid ones (Odedokun & Round, 2001; Barro, 2000; Vanhoudt, 2000; Deininger & Squire, 1998). All in all, it is essential to consider not only aggregated measures to analyse inequality but also contemplate measures that comprise micro determinants to evade wide-ranging statements that could overlook the true nature of inequality. At a micro level the plausible causing drivers of inequality are redistributive and labour market policies like social security, education, etc. (Becker, 1964; Rani, 2016) along with some other household characteristics including occupation, age, gender, race, marital status and residency of household (Mengesha, 2019; Charles-Coll, 2011; Fields, 2003; Bourgignon & Morrisson, 1998).

Recently, Rios Avila (2019) explored the factors that are responsible for wage inequality in the United States (US) using RIF regression. The finding of the study revealed that inequality in the US has increased steadily. When using Gini as a distributional statistic, the percentage of single-headed households, the number of children in the home, and the presence of minority households all significantly contribute to income inequality.

Dabla-Norris et al (2015) investigate the drivers of inequality for a sample of 100 advanced economies and Emerging Markets & Developing Countries (EMDCs) using five-year panels over the period 1980–2012. Their empirical findings show significant differences in inequality drivers among advanced economies and EMDCs. In advanced economies, rising skill premium is allied with income inequalities while in EMDCs financial deepening is a major contributor suggesting financial inclusion as a policy variable. Technological advancement and trade openness are significant in both types of economies contributing positively and negatively respectively.

Fournier & Koske (2013) investigated the determinants of inequality in wage-earning for thirty-two countries using quantile regression analysis. For most countries working hours appeared not only as an important determinant of individual’s earnings but also a significant contributor of inequality between working populations. The returns of experience measured by age and working an additional hour are highest for lower quantiles showing that overtime and experience play a noteworthy role in low-wage jobs. The role of sector composition in explaining cross-country differences in earning inequalities came out quite small. To narrow inequalities upper secondary, non-tertiary degree and permanent job status are found important determinants.

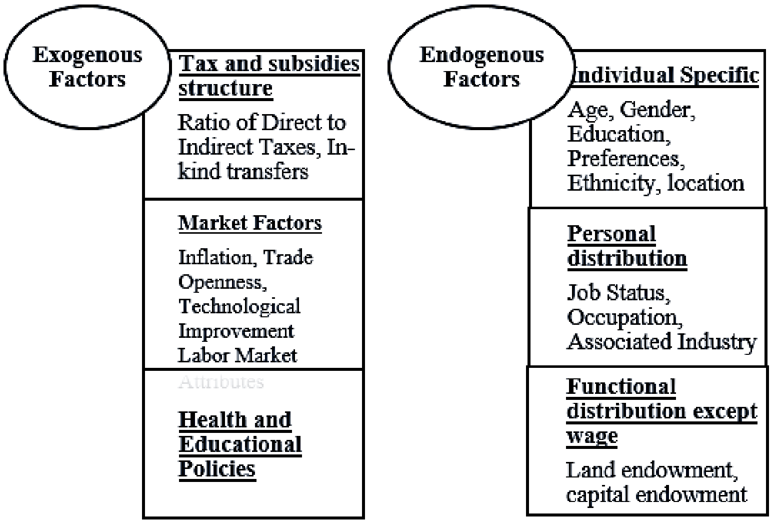
Alejo et al. (2011) estimate the distributive effect of education on various quantiles of income and the Gini coefficient for Argentina using three micro data sets for the years 1992, 1998 & 2008. During this period of consideration, Argentina goes through a drastic movement in inequality, poverty and other distributional aspects of income along with dramatic change in education. The study found that the effect of education on the distribution of income is heterogeneous and growing along the various quantiles. The results of conditional quantile regression revealed that these effects range from 0.63 to 0.095 for the first and nine deciles of income distribution respectively. The conditional quantile regression doesn't imply that education has a significant effect on upper quantile or rich instead it just concludes for conditionally rich, after controlling all covariates. As a result, it is quite difficult to believe that these unequalizing effects appear in the unconditional distribution of income. Therefore, Alejo et al (2011) also used unconditional quantile regression that shows an un-equalizing increase in inequalities measured by the Gini index. Overall, in the case of Argentina, the contribution of education was found positive in raising inequalities.

Jamal (2006) attempts to identify the determinants of inequality in Pakistan. He found a negative rapport between development expenditure and the level of inequalities. The results revealed that public expenditure especially expenditure on health and education certainly increases the accumulation of human capital and thus abridged income inequalities consistent with the view of Galor and Moav (2004). Further Improvement in agriculture terms of trade and direct-to-indirect tax ratio also negatively affect inequalities. In contrast GDP per capita, manufacturing to agriculture wage gap and inflation hurts income distribution. In Pakistan, high economic growth during the early 2000s was not pro-poor for the reason that it was not accompanied by lowering inequality. The prosperous person benefited more than the deprived. Hassine (2014) performed an empirical analysis, based on 28 household income and expenditure surveys for twelve Arab countries. The study estimates a set of inequality indicators derived from real monthly household per capita consumption expenditures and found no strong direct causal effects of inequality on Arab insurgency. To find out, how the disparities in households' characteristics have an effect on the level of consumption inequality over time and across regions study carries out a standard decomposition technique and reveals that rural/ urban location, educational status, and demographic composition measured by the size of the family are the most significant contributor of these type of inequalities in Arab Region. Based on in-depth information taken from a survey of 406 households Rahman (2015) looks at the extent to which regional and household aspects influence inequalities in income and consumption for twenty-one villages of Bangladesh. The study demonstrates that the socio-economic characteristics such as education of HOH significantly reduce consumption inequalities or raise welfare whereas the increase in dependency ratio left disadvantageous effects on it. Ownership of land appears most dominant variable that significantly elevates consumption. Moreover, income received from non-agriculture activities and diverse and new variety cultivation lessens inequalities in the distribution of income and significantly enhances consumption.

Framework of the Study

After scrutinising the literature, the conceptual framework for the study on probable causes of disparities in income and consumption distributions and their socio-economic consequences can be visualized in flow diagram 2. Here the factors that determine inequalities in a society are alienated into endogenous or exogenous factors. The endogenous factors are the individual-specific causes that could be best described as a set of circumstances intrinsic to individuals by whom the potential level of wealth or income of individuals is set off that also determines the consumption level. These factors include Individual attributes like age, race or ethnicity, level of education and preferences. Individual preferences are important to be considered here as they are influenced by the social and cultural values of the society. In a nutshell, preferences determine individual attitudes towards the choice of risk appetite and decision over leisure and work. The individual's job status measured by self-employed, paid employees and cultivators is introduced as a determining factor of personal distribution along with occupation and associated industry. The wage/earning differentials in these heads influence overall income inequality. The pattern of income differences widens even more if we include the functional distribution. Conceivably the most important causes of income inequality are the distribution of land and capital. The effects of disparities in endowments of these factors can be traced as a permanent provoker of inequalities. These factors not only create inequalities in outcome or current income but also lessen opportunities for those not holding them in future and have an effect on an individual's consumption choices.

Figure 2 Factors that cause Income/Consumption inequalities



Source: Author illustration

Moreover, education and health of individuals are the most significant determinants of inequalities, the prevailing policies for providing quality education and health to the masses can potentially influence the level of inequalities. A region with poor access to education and health could find itself in a situation in which the productivity of the majority of workers is very low and therefore the scarcity of skilled labour raises the wages of productive workers even further. Moreover, the excess supply of unskilled labour drives wages to even lower levels for them; consequently, the widening wage differential further deteriorates inequalities. Another exogenous cause of inequality is the size of the government budget and the amount that the government devoted to providing in-kind transfers and subsidies. The revenue collections via taxes also manoeuvre income distribution. A redistribution policy for equitable distribution demands a higher direct-to-indirect tax ratio and more specifically it requires a progressive tax structure. Adaptation of new advanced technology will also lead to higher income disparities because few persons can benefit from this new technology until its trickle-down effects become prominent. Similarly, financial sector development also provokes inequality in the initial period but later it provokes equality when the majority of people have accessibility to credit (Greenwood & Jovanovich 1990). Globalization reflected by openness also significantly contributes to framing distribution patterns. The Heckscher-Ohlin and Stolper-Samuelson theorems provide theoretical support for it. According to the theorem labour demand shifts from unskilled to skilled workers as openness increases in the case of developed nations because of specialization in the production of Skill intensive products. The contrasting effects on underdeveloped nations are not supported unambiguously by empirical literature.

The effect of income inequalities on the growth process is found ambiguous in the literature. Both positive as well as negative effects of inequality are probable depending on the mechanism or cause by which inequalities originate. The inequalities resulting from unequal opportunities are detrimental to sustainable growth while unequal outcomes generate obligatory incentives for capital accumulation and economic growth (WDR 2006). Similarly, income inequalities due to poor socio institutional factor is expected to have negative effects on growth however "Market inequality"- due to market forces is expected to have positive effects (Easterly 2007). The enlarged income disparities may lead to various other devastating consequences which in turn may impede the growth process. The increase in crime rate is one of the disparaging consequences of income inequalities. The relative deprivation of the unprivileged class may cause frustration and anger that unloads itself in violent crime. Merton (1938) put forward the strain theory which implies that lack of legitimate means to accomplish common social goals for the poor breed crimes. Concisely an inequality of opportunities is a driving force of crime. Inequalities also lower social mobility by providing the privileged class more resources for securing desirable positions for them. Higher-income families can more readily afford lavish housing and neighbourhoods with access to high-quality social services that assist in human capital formation so their children remain in the upper region of the class distribution (Durlauf

1996). In contrast, the extreme opposite income class has relatively fewer incentives to climb up the class ladder.

Method and Material

The empirical examination utilizes the household survey data conducted by the Pakistan Bureau of Statistics (PBS). This research allied household income and consumption expenditures to the characteristics of household and labour market. The choice of determinants is initially stimulated by the seminal literature of Mincer (1958, 1974), who used schooling, age and working hours to explain the parsimonious labour earning model. Several other drivers of earning and consumption have also been added to the model, including gender of head of household, gender of highest earners, dependency ratio, employment status, occupation, net remittances, social protection etc. To estimate the model this study will use both conditional and unconditional quantile Regression methods. Conditional quantile regression gives support to understanding the effect of explanatory variables along the distribution of the outcome variable as the different characteristics might leave different impacts on low and high-income households. Consequently, conditional quantile regression is well-liked in the empirical literature that focuses on assessing the effect of different explanatory variables on the conditional distribution of income or consumption. Unlike the OLS estimates conditional quantile regression does not follow the law of iterated expectation, therefore their estimates do not average up to the unconditional mean and fail to give any idea about the distribution statistics. The policy-oriented research is most likely interested in distributional statistics and how different factors alter these distributive statistics. The unconditional quantile regression is worthwhile to address such a question. It provides estimates that delineate the impact of explanatory variables on individual quantiles of the unconditional distribution of dependent variables. Hence, in contrast to the results obtained from quantile regression that are not generalizable in the context of population or policy framing the unconditional quantile regression estimates give more generalizable results as it marginalizes the effect over the distribution of independent variable.

In this study, the dissimilarities among these two regression models are pointed out theoretically as well as econometrically by estimating both models using Household Integrated Economic Survey (HIES) survey data conducted by PBS for the year 2018-19.

Conditional Quantile Regression (CQR)

To examine the partial effects of exogenous variables on whole distribution rather than examining the average effect the methodology proposed by Koenker and Bassett (1978) proved to be a valuable contribution to empirical literature. CQR has the potential to capture heterogeneity in the effect of the explanatory variables on the outcome that ordinary least square (OLS) estimates ignore and therefore provide only the mean effect of a specific independent variable. In contrast, CQR is a powerful tool to compare various aspects of a particular distribution of outcome variables, across different covariates patterns. The conditional quantile model assumes that the conditional quantile of a random outcome variable $\mathcal{Y}$ is a linear function of independent variable $\mathcal{X}$ (Koenker and Bassett; 1978). A linear regression model for the τ^{th} conditional quantile of $\mathcal{Y}_i$ is expressed as

$$Q_{\mathcal{Y}_i(\tau)|x_i}=\mathcal{X}_i\,\alpha_\tau \tag{1}$$

Here $\mathcal{Y}$ is a scalar vector of the dependent variable, $\mathcal{X}_i$ is the N x1 vector of the independent variable, α is the coefficient vector and τ demonstrates the conditional quantile of interest. Assuming $\mu_{i,\tau}$ is the residual of τ^{th} quantile regression model.

$$Q_\tau(\mu_{i,\tau}|x_{i,\tau}) = 0 \tag{2}$$

In contrast with the classical linear model that is based on the minimization of the residual sum of squares, the conditional quantile regression minimizes the asymmetrically weighted absolute residuals. Therefore, the parameter of quantile regression $(0 < \tau < 1)$ can be estimated as

$$min\ \left[\ \sum_{\mathcal{Y}_i \geq \mathcal{X}_i\alpha_\tau} \tau(\mathcal{Y}_i - \mathcal{X}_i\alpha_\tau) + \ \sum_{\mathcal{Y}_i \geq \mathcal{X}_i\alpha_\tau} 1-\tau(\mathcal{Y}_i - \mathcal{X}_i\alpha_\tau)\right] \tag{3}$$

The case of $\tau = 0.5$ provides the results in terms of median, whereas any value of τ between zero and one permits to analyse the dependence structure at any location of the conditional distribution. The estimated parameters of the conditional quantile regression can be interpreted in the same way as the parameters of the OLS model. Each α coefficient shows the average rate of change in the τ^{t} quantile of the distribution of the dependent variable in response to a unit change in the value of regressors, holding the assumption of ceteris paribus.

Unconditional Quantile Regression

Unconditional quantile regression (UQR) is used to model unconditional quantiles of outcome variables being a function of regressors. The concept of unconditional quantile regression occupied a prominent place in the literature regarding income and inequalities, labour economics and public policy etc, particularly in the context of analysing the distributional effects on outcome. Firpo et al (2007 & 2009) have made a seminal contribution in this respect by giving the methodology regarding the assessment of the partial effect on the unconditional distribution of regresand Y, due to changes in the distribution of regressors X, using Re-centered Influence Functions (RIFs).

Re-centered Influence Function (RIF)

Researchers are usually concerned about the changes in quantile Q_τ of unconditional distribution. Assuming the cumulative density function as $F_y\ (\cdot)$ and probability density function as f_y (.) the required information for analysing distribution can be written in the form of a vector as

$$F_y = [\{\mathcal{Y}, F_y(\mathcal{Y})\} | \mathcal{Y} \in \Re] \text{ or } f_y = [\{\mathcal{Y}, f_y(\mathcal{Y})\} | \mathcal{Y} \in \Re] \quad (4)$$

Here $\mathcal{Y}$ represents income. It shows that any distributional statistics can be derived if one has access to any of these vectors of information ($\mathcal{Y}$, F_y & f_y). Hence, to measure the change in the distributional statistics the Cdf of observed distribution F_y and contaminated distribution C_y can be compared

$$\Delta v = v\,(C_y) - v(F_y) \quad (5)$$

Here Δv is the change in the distributional statistic as a result of a change in distribution from $F_y \rightarrow C_y$. The extent of change depends on the size of the population therefore to overcome this the standardised change will be computed as

$$\Delta^S v = \frac{\Delta v}{\Delta(C_y - F_y)} = \frac{v\,(C_y) - v(F_y)}{\Delta(C_y - F_y)} \quad (6)$$

It can further be extended to measure $\Delta^S v$ for an infinitesimally small change in the distribution function from $F_y \rightarrow C_y$. Assuming that at the contamination point, the observation included in the sample has an income $\mathcal{Y}_c$.Given that it is a single observation the cumulative density function may be written as

$$H_{Y_c}(\mathcal{Y}) = 0 \;\forall\; \mathcal{Y} < \mathcal{Y}_c \;\&\; H_{Y_c}(\mathcal{Y}) = 1 \;\forall\; \mathcal{Y} \geq \mathcal{Y}_c \quad (7)$$

By combining the observed distribution F_y and H_{Y_c} one can construct the distribution that can be observed by C_y.

$$C_y = (1-\varepsilon)\,F_y + \varepsilon(H_{Y_c}) \quad (8)$$

Using the above equation, the change in the distribution can also be quantified, as ε, when moving from $F_y \rightarrow C_y$. Further, with this last concept in place, the formal definition of the IF can be written as

$$\text{IF}\,[\mathcal{Y}_c;\, v(F_y)] = lim_{\varepsilon \to 0} \frac{v[(1-\varepsilon)F_y + \varepsilon(H_{Y_c})] - v(F_y)}{\varepsilon} = \frac{\partial v(F_y \to H_{Y_c})}{\partial \varepsilon} \quad (9)$$

The influence function is a directional derivative that shows the changes in distributional statistics v in response to the small change in F_y. IF would be different for each contamination point. It indicates that given more weight to observation with income Y_c, the mean μ would change at a rate of $Y_c - \mu_y$. Moreover, considering a change in the distribution equal to ε the change in the mean will be

$$\Delta\mu = \varepsilon\ x\ \text{IF}\,[\mathcal{Y}_c;\, v(F_y)] \quad (10)$$

Rather than using IF, Firpo et al (2009) recommend Re-centered Influence Function (RIF) stated as

$$\text{RIF}\,[\mathcal{Y}_c;\, v(F_y)] = v(F_y) + \text{IF}\,[\mathcal{Y}_c;\, v(F_y)] \quad (11)$$

The RIF specifies the relative contribution of contaminated observation Y_c on the construction of distributional statistics v. also it can be interpreted as the approximation of distributional statistics v taking into consideration the influence of Y_c. The IF and RIF have some properties that the expected value of IFs is equal to zero which in turn implies that the expected value of RIFs is equivalent to the distributional static itself (Firpo et al. 2009; Essama-Nssah & Lambert 2012; Cowell & Flachaire 2015).

RIF Regression

As mentioned earlier, the IFs and RIFs used as a tool to illustrate statistical inferences (Hampel; 1974). Firpo et al (2009) recently used Re-centered Influence Functions (RIFs) to estimate RIF regressions. To measure the unconditional partial effects of small change in the distribution of covariates X on the distributional statistics υ Firpo et al (2009) used this strategy using a linear model. The insight of this RIFs regression can be illustrated by assuming the joint distribution function that describes the linear or non-linear association among the dependent variable $\mathcal{Y}$ and covariates X.

$$dF_{y,x}(\mathcal{Y},X) = dF_{y|x}(\mathcal{Y}|X=x)\, dF_x(X) \quad (12)$$

Using the above equation, the cumulative distribution function (CDF) may be written as

$$F_y(\mathcal{Y}_i) = \int F_{y|x}(\mathcal{Y}_i|X=x)\, dF_x(X) \quad (13)$$

This simply states that the unconditional CDF of $\mathcal{Y}$ can be attained by integrating (averaging) the conditional distribution $F_{y|x}(.)$ across all possible realizations of X. Further it implies that if $F_{y|x}(\mathcal{Y}|X)$ is assumed to be constant then change in the distribution of covariates $F_X \rightarrow C_X$ will alter the unconditional distribution of $\mathcal{Y}$.

$$C_y = \int F_{y|x}(\mathcal{Y}_i|X=x)\, d\, C_x(X) \quad (14)$$

It will further translate into a change in the distributional statistic υ which is measured by averaging the RIFs through the changes in the distribution F_y

$$\upsilon(F_y) = hE\left[RIF\left(\mathcal{Y}, \upsilon(F_y)\right)\middle| X=x\right] dF_x(x) \quad (15)$$

The above equation is proposed by Firpo et al. (2009) for validating the use of RIFs in the context of regression analysis. The distinguishing feature of RIF regression is that it uses the estimated RIF $[\mathcal{Y}_i;\, \upsilon(F_y)]$ for each value of $\mathcal{Y}_i$ as the dependent variable.

$$\upsilon(F_y) = \text{RIF}\,[\mathcal{Y}_i;\, \upsilon(F_y)] = \beta X_i + \varepsilon_i \quad (16)$$

The unconditional partial effects on the distributional statistics can be obtained by taking unconditional expectation on both sides of the above-mentioned equation

$$\upsilon(F_y) = \text{E}\,[\text{RIF}\{\mathcal{Y}_i;\, \upsilon(F_y)\}] = \text{E}\,(\beta X_i) + E(\varepsilon_i) \quad (17)$$

As we know the expected approximation error is equal to zero, therefore

$$\upsilon(F_y) = \text{E}\,[\text{RIF}\{\mathcal{Y}_i;\, \upsilon(F_y)\}] = \beta \bar{X}_i \quad (18)$$

$$\beta = \frac{\partial \upsilon(F_y)}{\partial \bar{X}_i} \quad (19)$$

That is, if the distribution of covariates changes marginally, the expected change in the distributional statistic is equal to β. A significant application for our case corresponds to the effects of X on the unconditional quantiles of $\mathcal{Y}$ or any function of unconditional distribution of income e.g. Gini index. Assuming $\upsilon(F_y) = \mathcal{Q}_\tau$ be a symbol of τ^{th} quantile of F_y, RIFs can be written as

$$\text{RIF}\,[\mathcal{Y}_c;\, \mathcal{Q}_\tau] = \mathcal{Q}_\tau + \text{IF}\,[\mathcal{Y}_c;\, \mathcal{Q}_\tau] \quad (20)$$

$$\mathcal{Q}_\tau = \text{E}\,[\text{RIF}\{\mathcal{Y}_i;\, \mathcal{Q}_\tau\}] = \text{E}\,(\beta X_i) + E(\varepsilon_i) \quad (21)$$

$$\mathcal{Q}_\tau = \text{E}\,[\text{RIF}\{\mathcal{Y}_i;\, \mathcal{Q}_\tau\}] = \beta X_i \quad (22)$$

The last expression is the unconditional quantile regression that links the expected value of τ^{th} quantile, which is measured by using RIF, to explanatory variables.

Variable Description and Data Used

The study focuses mainly on the endogenous factors influencing changes in income and consumption distribution patterns. These endogenous factors are described under three heads that include demographic, functional income factors, and opportunities. We take into account a wide range of potential variables in all the above-mentioned heads, driven by past empirical studies. The exogenous transfers received by households in the form of public assistance and remittances are also part of all regression models. The model presented below is used for conditional quantile regression (CQR) and unconditional quantile regression (UQR) both.

$$\left.\begin{matrix} lnPCY\_Eq_{ij} \\ lnPCC\_Eq_{ij} \\ Gini_i \end{matrix}\right\} = \alpha_{ij} + \sum_{k=1}^{n}\beta_k D_{ij} + \sum_{k=1}^{n}\beta_k TP_{ij} + \sum_{k=1}^{n}\beta_k O_{ij} + \sum_{k=1}^{n}\beta_k FIS_{ij} + \mu_{ij} \quad (23)$$

Where *i* stands for regional levels, such as provincial (i=1, 2, 3, & 4, signifying four provinces) *and national (i=0). j* stands for the quantile for which the model is regressed. Ln_pcy_eq and ln_pcc_eq are the log of per capita equalized income and consumption of the household while Gini is a distributional statistic to account for income and consumption inequalities in unconditional quantile regression. Variables used in the regression are categorized under four sub-heads that are demographics (D), opportunities (O), transfer payments (TP) and functional income sources (FIS) of the household. *k* is the number of indicators under each head.

Figure-3 Classifying variables used in regression

Endogenous Factors

- **Demographic Factors**
  - Single Headed Household
  - Occupancy Status
  - Age of highest Earner
- **Functional income Factors**
  - Interest income received by household
  - Dummy to shows whether household received rental income or not
- **Rights to use Opportunities**
  - Female labour force participation rate
  - Access to Basic services
  - No of employed persons in high paid occupation (Managerial and professionals)
  - No of employed persons in low paid occupation
  - Ratio of employed person who has received technical training
  - Possession of Large &small Assets
  - Average years of schooling

Exogenous Factors

- **Transfers to Household**
  - Net remittances received by Household
  - Public Assistance received by household

Source: Author's illustration

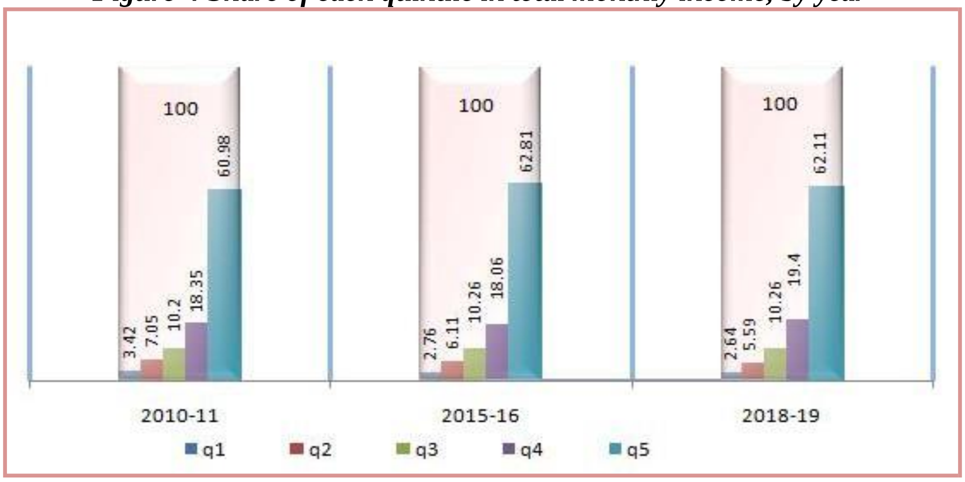
Empirical Results

We began this section by providing some stylized facts about the distribution of income and consumption and by giving some descriptive analysis of variables used in the estimation process. Further, this section proceeds by discussing the estimated results of conditional and unconditional quantile regressions.

Descriptive Analysis

The individuals' life prospects and the future of their coming generation are largely influenced by their income, wealth and the level of consumption. The aggregate measures of inequality such as -the Gini index do not indicate whether the increasing or declining inequalities are the result of change at the top, bottom or middle of the income distribution. These measures portray only the partial picture therefore inter and intra quintile analysis is effective to understand the nature of these disparities.

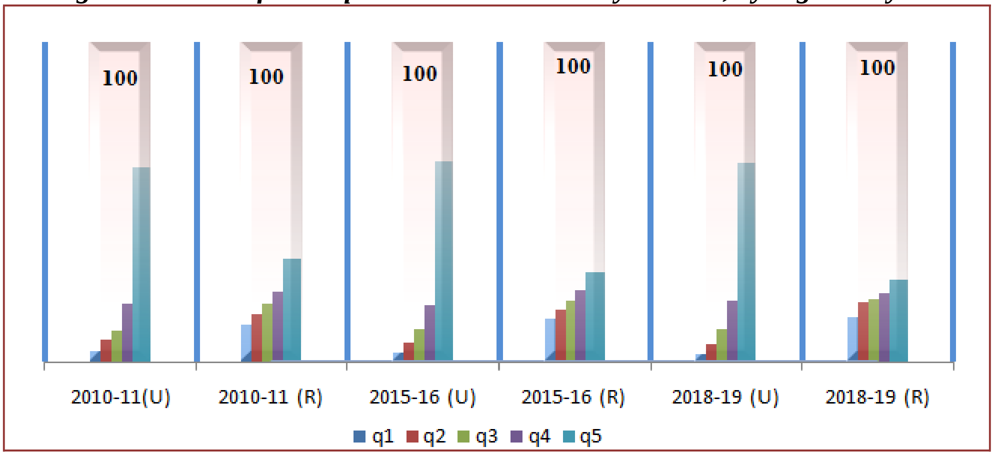
Figure-4 Share of each quintile in total monthly income, by year



Source: Author's estimation

Figure 4 shows the percentage distribution of monthly income by quintile. The share of income going to the top two quintiles shows a decreasing trend with data from 2010-11 to 2018-19, while the bottom three quintiles experience an increasing trend. The bottom three quintiles together comprise only 36.24% monthly income share as compared to the highest quintile.

Figure-5 Share of each quintile in total monthly income, by region & year



Source: Author's estimation

At the regional level, the data (Figure 5) revealed that the dispersion in the percentage distribution of monthly income by quintile is more pronounced in urban areas relative to rural areas. The urban labour force is usually more diverse in terms of skill and level of education as compared to its rural counterpart, further income from self-employment is more concentrated in urban areas and this self-employment ranges from wealthy investors to poor workers whereas the majority of rural self-employed are homogeneous and mostly in informal sector enterprises all these are the potential factors behind this rural-urban divergence.

The explanatory variables for the conditional and unconditional quantile regression have been selected based on previous research and data availability. The Table-1 shows deviations in these variables across income quintiles.

Table 1 Quintile-wise variable description

Variable Description	Quintile-1	Quintile-2	Quintile-3	Quintile-4	Quintile-5
Percentage of single-headed household	46.8	9.18	9.81	12.76	21.45
The average age of the highest earner	40.4	39.9	40.3	40.9	43.7
Average equalized household Size	7.8	7.9	7.4	7.0	6.3
Percentage of households live in rented houses	14.34	15.17	18.55	23.82	28.12
Percentage of households live in their own house	20.95	20.79	20.25	19.35	18.66
Percentage of households received interest income	10.08	8.82	5.67	8.44	67
Percentage of households received rental income	25.76	12.71	15.07	16.79	29.67
Average female labour force participation rate	20.62	22.69	18.02	13.94	14.06
A percentage of the population has access to basic services	5.33	3.73	10.58	27.85	52.51
Percentage of employment in the high-paid occupation	3.08	5.68	10.05	18.83	62.37
Percentage of employment in the low-paid occupation	13.93	19.74	21.26	23.35	21.71
Percentage of household paid remittances	8.27	5.99	7.88	12.06	65.80
Percentage of households received remittances	54.38	13.42	11.74	10.33	10.14
Percentage of households received	32.95	29.53	21.22	11.5	4.79

Variable Description	Quintile-1	Quintile-2	Quintile-3	Quintile-4	Quintile-5
public assistance					
Percentage of the population with training	11.49	12.08	19.17	23.25	34

Source: Author's estimation

The proportion of singled-headed households is highest in the lowermost quintile along with having a higher equalized household size as compared to the upper quintiles. Moreover, individuals in lower quintiles are usually engaged in low-paid occupations. This suggests that there are comparatively more people to feed in lower-income quintiles, and female labour engagement in these quintiles is also encouraged to satisfy the family's financial demands. The income of the households in lower quintiles is also supplemented by receiving rental income, remittance and public assistance more than those in the upper quintiles. However, the proportion of households receiving interest income from savings and investments is higher in the upper quintiles. Further individuals belonging to lower quintiles are also relatively much deprived of basic service provision including gas, electricity, clean drinking water and sanitation.

Regression Results

The factors that are accountable for prevailing inequalities in Pakistan are explored using conditional and unconditional quantile regression. For the analysis average per capita equalized log income and average per capita equalized log consumption are used as dependent variables. The variables that encapsulate household characteristics are used as explanatory variables. Regression results are displayed in accordance with the classification of regressors generated in the aforementioned flow for the logical understanding of the regressors. Moreover, the results are presented comparatively not only along quantiles and techniques used for estimations that is conditional quantile regression versus unconditional quantile regression but also at spatial levels such as national (Annex Table A2 & A3 representing results of income and consumption respectively) and provincial level (Annex Table A4 & A5, Table A6 & A7, Table A8 & A9 and Table A10 & A11 for KPK, Punjab, Sindh and Balochistan respectively).

OPPORTUNITIES

The impacts of schooling are varied and rising along the quintiles, which is consistent with most previous findings. The effects of the conditional distribution of income, according to CQR data, range from 3.6% for the first quintile to 4.8% for the final quintile (Annex Table A2). This finding should be viewed with caution. It just implies that, after controlling for confounders, when education is improved by one year, all quantiles of the conditional distribution grow, but at a faster pace for the higher quantiles. The top (bottom) of the conditional distribution does not overlap with the top (bottom) of its unconditional counterpart, which is a common challenge in interpreting these results. That is, the positive and varied CQR effects do not imply that education has a stronger effect for the rich, but the conditionally rich, that is, after all factors have been controlled for. As a result, it's impossible to tell whether this unequal effect translates into the unconditional distribution of income or not.

The UQR technique, which investigates this effect directly on income distribution, is often considered meaningful in such cases. UQR results indicate even more pronounced diverse behaviour, with increasing standard deviation from 0.5% to 2.08%. The UQR results are more easily interpreted because they clearly show that education has a greater impact on the upper quantile. Finally, using Gini as a distributional measure, RIF regression results show that marginally increasing the distribution of education leads to an un-equalized increase which exacerbates equalities at the national level. Moreover, the return to a marginal increase in education on consumption is also found statistically significant both in CQR and UQR results (Annex Table A3). The implication is that a household's average years of schooling are positively associated with increased consumption, but the impacts vary by quintile therefore the distributional statistic (Gini) increases. The percentage of technically skilled people in the household appears to have an insignificant effect on the Gini coefficient of income and consumption distribution nationally. The conditional and unconditional quintile regression results for all quintiles are though found statistically significant at one percent level indicating that an increase in the proportion of technically proficient workers enhances the share of income owned by each quintile. This implies that a marginal increase in the proportion of technically trained household members shifted the income and consumption distribution of each quintile upward but left the overall distribution unchanged. The results of both CQR and UQR reveal that access to basic services such as clean fuel, electricity, safe drinking water, sanitation, and waste disposal may not have an inclusive effect because the poor have not benefited sufficiently from it. Increases in basic amenities have a large positive impact on each quantile's income and consumption, but the effects are not evenly spread across all quantiles, resulting in greater disparities in consumption and income distribution, even though consumption inequalities increase with relatively higher magnitude than income inequalities.

An essential determinant of income and consumption inequality especially related to labour market opportunities, is the percentage of women associated with the labour market. As per income quintile, regression estimates marginal return to increase in female participation in the labour market by 1% vary substantially across quintiles. Higher returns are observed for the higher quintile while returns decrease as we move towards the lower income quintile, after controlling for confounders. The results of unconditional quantile regression suggest that an increase in the rate of female participation worsens the distribution of income. The other models of unconditional regression also suggest the same. For the lower two quintiles, the effects are negative while for the upper two quintiles, the effects are positive indicating a significant difference between the upper and bottom income distribution. The same is true in the case of consumption inequalities but the increase in the value of Gini is about 22% less in the case of consumption inequalities in comparison with income inequalities.

Having a member of the household employed in a managerial position would raise the per capita income of the household by approximately 26% while having one employed in clerical and skilled positions would result in an increase in per capita household income by around 6% in general for all quantile as per CQR. However, as the income of individuals in the upper quintile is higher relatively, this percentage increase in income because of being employed in managerial and clerical work would be greater in absolute terms. As far as UQR outcome is concerned it can be seen that the equality of distribution is directly related with having being employed in clerical work as this employment encompasses the majority of the lower quintile workers while it is inversely related with being having household members in managerial work because this would result in expanding inequalities. The findings of consumption regressions demonstrate the same conclusion that is drawn out from income regression after controlling the other factors, but the effect of being employed in different sets of occupational groups remains relatively larger for income distribution than consumption distribution. Moreover, the possession of small and large assets may significantly affect the distribution of income and consumption expenditures. The increasing income and consumption inequalities are generally associated with the increase in the possession of large assets whereas a marginal increase in the possession of small household assets helps significantly to improve income and consumption distribution.

Annexure Tables A4 to A11 present the findings of conditional and unconditional quantile regression for the four provinces of Pakistan. In general, the calculated coefficients of education, employment at the managerial position, employment at the clerical and skilled position, access to basic services and participation of women in the labour market have the almost same sign and magnitude as those obtained in country level regression.

Demographic Factors

The age of the highest earner has a significant positive effect on HH income and consumption. As an individual ascends in age, they become more experienced thus their income rises and so does their consumption. One notable finding of the regressions is that population ageing may have a long-term detrimental impact on income inequality. If the age of the highest earner increases marginally it improves equality of earning and therefore the value of the Gini coefficient declines significantly. As per the results of conditional quantile regression ageing increases the income of the lower three quintiles but this increase is at a decreasing rate while the per capita income of the uppermost quintile decreases at an increasing rate. Thus, both conditional and unconditional quantile regression are in line with theory as Pakistan's demographic structure mostly comprises of youth population therefore ageing has positive significant effects on the distribution of income especially for the lowest quintile whose population growth rate is relatively higher than other counterpart. Although, the change in consumption is more inclined towards the upper quintiles. Thus, its effects on the distributional statistic are rather distorting equality of consumption distributions. Moreover, the marginal increase in single-headed households also has a negative impact on income and consumption distribution. Owned occupancy resembles wealth and wealth is inversely related to work hours supplied by household. Therefore, compared to rent-paying households, owned-occupancy households have comparatively lower incomes, which leads to decreased consumption.

The coefficient of linear and quadratic age components included in the conditional and unconditional quantile regressions for the province of Pakistan show that the returns to age vary greatly between provinces. In KPK and Balochistan, the age structure of the highest earner contributes considerably to reducing income discrepancies. The results of KPK and Balochistan are similar to national-level conclusions but in contrast, ageing contributes positively to magnifying both income and consumption inequality in Sindh. The returns of increasing age vary significantly across quintiles in Sindh, especially for the lower two quintiles increase in age reduces per capita income by one percentage point and therefore leaves a positive significant effect on distributional statistic Gini.

Functional Income Sources

Income from owned factors of production is crucial in defining the living standard of a household and framing its income and consumption patterns. Savings, securities investments, and lending activities provide interest income for households. Moreover, through renting their assets such as land, houses and other owned capital resources households receive rental income. Rental income is proportionally linked with per capita equalized consumption while inversely related to per capita equalized income of the household in lower quintiles and positively linked with upper quintiles in general. Thus, increase distributional inequalities. In general, interest income is positively associated with both equalized income and consumption. This can be rationalized as interest income from savings, securities and lending are subject to high market volatilities especially when it comes to the downside risks than rental incomes that are usually more reliable and have less fluctuating downside. Thus, a household is more likely to alter its supply of labour based on rental income rather than interest income. In a nutshell, having income from functional sources would increase income and consumption distributional inequalities as ownership of these functional resources is unequal in Pakistan. These results remain valid at the Provincial level as well.

Transfers to Household

To account for the transfers made to the household either by public or private sources two indicators are included in all regressions. The first is the public assistance incorporating public transfers such as BISP which constitute the majority of these transfers, zakat and other governmental transfers. The national results indicated that as more public assistance is received by the household members, the equalized per capita income and per capita consumption both decline though the decline in income is greater than that in consumption. This stands in line with the theory of labour supply which suggests that a rise in non-labour income will make individuals reluctant towards work and results in decreasing labour hours supplied. Interestingly for upper-income quintiles, the result remains more or less similar. Around 4.7% of the households receiving public assistance, which majorly holds BISP transfers, belong to the uppermost quintile. It is worth mentioning, however, that a sizable fraction of wealthier households get BISP financial support, raising concerns about the program's targeting effectiveness (Farooq 2014). The second indicator used for transfer payments to households is the remittances received by it. The outcomes of this variable across conditional and unconditional income quantile regression results are also in accordance with the theory as in the case of public assistance though its impact on distributional statistics of consumption is insignificant in contrast to public assistance which exaggerates distributional inequalities.

Furthermore, with the exception of Balochistan, transfers to households in the form of public assistance contribute significantly to exaggerating income and consumption disparities at the provincial level. For KPK, Balochistan and Sindh increases in public assistance have a detrimental influence on all quintiles earning capacity excluding the uppermost quintile for Punjab. Remittances serve a significant role in determining income disparity in all provinces since increased remittances lower income and hence increase income disparities. When looking at the consumption, it can be observed that a marginal increase in remittances is positively associated with consumption expenditure for all consumption quintiles consequently improving consumption distribution in Punjab province, while having no effect on consumption distribution in other provinces.

Conclusion

Given the recent resurgence of interest in reducing inequality as a way of combating poverty and achieving SDGs in Pakistan, together with the scarcity of prior empirical research on inequality based on data from the area, this research examines the contributing factors of income and consumption disparity at the national provincial and regional level. Economic inequalities occur primarily as a result of the sluggish rate of growth and inequitable distribution of the tiny benefits of progress, both of which are impacted by economic and non-economic variables. Even the benefits of planned development passed majorly towards already developed regions because of the requisite infrastructure that draws more investment. Within such locations, advantages accrued proportionately more to the already wealthy and socially privileged, reinforcing social inequities and income and consumption distribution imbalances. These inequalities are defined as the outcome of the interaction of endogenous and exogenous factors that influence individuals and demographic groups at the same time.

The empirical assessment is based on the household income and expenditure survey data collected by the Pakistan Bureau of Statistics for the year 2018-19. The quintiles are used as a fundamental unit of analysis to look at how social and economic variables evolve in connection to people's well-being over time. For the formulation of development policies, the government needs to know if poorer families have access to fundamental services (safe drinking water, sanitation, electricity and so on) or if there are substantial disparities between the affluent and the poor. Furthermore, policymakers want to know how poorer households' spending habits and income sources differ from those of wealthier households. Estimates by quintiles describe distributional disparities, making them a useful analytical tool. The arguments and the evidence provided in this study indicate that distributional inequalities either measured by consumption expenditure or income are affected by many endogenous as well as exogenous factors. The empirical investigation has drawn several analogous outcomes that are prevalent at the national and provincial levels, allowing for some broad generalizations to be drawn from the analysis. The following are the key conclusions drawn from the research:

- The data demonstrated that in urban regions compared to rural areas, the dispersion in percentage distribution of monthly income by quintile is more pronounced.
- The regression findings indicated that schooling has a variety of effects that increase as we move through the quintiles. Marginally rising educational distribution leads to unequal growth in inter-quintile income and consumption, accentuating national disparities. Overall distribution disparities remained unaffected as household members in each quintile acquired technical training even though it has a positive impact on income and consumption distribution in each quantile.
- Access to basic services has a significant positive effect on each quantile's income and consumption. However, the effects are unevenly distributed across quintiles consequently responsible for deteriorating income and consumption equalities. Furthermore, the distribution of income and consumption expenditures can be greatly influenced by the possession of small and large assets. Increases in the ownership of large assets are often related to growing income and consumption disparities, but marginal increases in the ownership of small family assets tend to improve income and consumption distribution substantially.
- The marginal return to increased female labour market participation varies significantly with quantile. The higher the income quantile, the greater the return, whereas the lower the income quantile, the lower the return. As a result, the income and consumption distribution is worsened.
- The equality of distribution is directly related to having a household member working in clerical work, as this occupation employs the majority of the lower quintile workers, whereas it is inversely related to having a household member working in managerial work, as this would result in increasing inequalities.
- For lower quintiles the returns to age are higher, with the view that age terms express an individual's work experience, this suggests that work experience is more important in lower-paying jobs.

- Having other sources of income and receiving unilateral transfers embellished disparities in the case of Pakistan because ownership of these other income sources like land and capital ownership are uneven in Pakistan.

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Annexure

Table A1: Variables description and their symbols

S. No.	VARIABLES	DESCRIPTION OF VARIABLES
1	Gender	Gender of the individual
2	age_he_hh	Age of the highest earner in the household
3	sq_age_he_hh	Squared age of the highest earner in the household
4	d_intt_ssl	Dummy equals 1 if interest income is received by household otherwise 0
5	yrs_edu_wap	Average years of schooling
6	d_highpaid_occ	No of employed persons in high paid occupation (Managerial and professionals)
7	d_lowpaid_occ	No of employed persons in low paid occupation
8	d_pub_ass	Net remittances received by Household
9	s_asset	Possession of small Assets by the household
10	l_asset	Possession of large Assets by the household
11	d_remit	Public Assistance received by household
12	d_occupancy_st	Dummy for Occupancy Status
13	d_rentY	Dummy to shows whether household received rental income or not. 1 if yes 0 otherwise
14	d_shh	Dummy equals 1 if the household is single headed household
15	P_tech_train	Ratio of employed person who has received technical training
16	fe_paricipation	Female labour force participation rate
17	d_access_BS	Dummy equals 1 if household have access to Basic services

Table A2: Average Per Capita Equalized Income Regression Results for Pakistan

DV:ln_apcy_e (Income)	**Conditional quantile regression**				**Unconditional quantile regression**				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	0.00584*	0.00950***	0.00296	-0.000399	0.00984**	0.00340	0.00542	0.00560	-0.000243
	(0.00342)	(0.00296)	(0.00302)	(0.00382)	(0.00423)	(0.00354)	(0.00381)	(0.00498)	(0.000188)
age_he_hh	0.00686***	0.00515***	0.00302***	-0.000404	0.00565***	0.00378***	0.00112	0.00715***	-0.000253***
	(0.000722)	(0.000611)	(0.000614)	(0.000763)	(0.000866)	(0.000725)	(0.000781)	(0.00102)	(3.84e-05)
sq_age_he_hh	-6.52e-05***	-4.27e-05***	-1.05e-05	3.72e-05***	-5.91e-05***	-2.91e-05***	7.69e-06	-3.74e-05***	3.44e-06***
	(8.26e-06)	(6.97e-06)	(6.96e-06)	(8.56e-06)	(9.85e-06)	(8.25e-06)	(8.88e-06)	(1.16e-05)	(4.37e-07)
d_intt_ssl	0.326***	0.358***	0.384***	0.512***	-0.0871***	-0.0485**	0.174***	0.573***	0.0319***
	(0.0210)	(0.0181)	(0.0185)	(0.0233)	(0.0259)	(0.0217)	(0.0234)	(0.0305)	(0.00115)
yrs_edu_wap	0.0355***	0.0425***	0.0444***	0.0468***	0.0233***	0.0304***	0.0444***	0.0685***	0.000980***
	(0.000619)	(0.000543)	(0.000571)	(0.000752)	(0.000785)	(0.000658)	(0.000708)	(0.000924)	(3.49e-05)
d_highpaid_occ	0.233***	0.238***	0.259***	0.291***	0.0667***	0.113***	0.201***	0.408***	0.0109***
	(0.00889)	(0.00769)	(0.00785)	(0.00993)	(0.0110)	(0.00920)	(0.00991)	(0.0129)	(0.000488)
d_lowpaid_occ	0.0636***	0.0574***	0.0560***	0.0611***	0.0970***	0.0963***	0.0847***	0.0421***	-0.00308***
	(0.00438)	(0.00379)	(0.00387)	(0.00489)	(0.00541)	(0.00453)	(0.00488)	(0.00637)	(0.000240)
d_pub_ass	-0.106***	-0.118***	-0.133***	-0.152***	-0.240***	-0.166***	-0.148***	-0.0564***	0.00533***
	(0.00545)	(0.00471)	(0.00481)	(0.00609)	(0.00674)	(0.00564)	(0.00607)	(0.00793)	(0.000299)
s_asset	0.0447***	0.0453***	0.0442***	0.0416***	0.0643***	0.0590***	0.0532***	0.0346***	-0.00111***
	(0.000904)	(0.000778)	(0.000794)	(0.00102)	(0.00111)	(0.000930)	(0.00100)	(0.00131)	(4.93e-05)
l_asset	0.0817***	0.0849***	0.0904***	0.0993***	0.0356***	0.0551***	0.0807***	0.126***	0.00279***
	(0.00105)	(0.000903)	(0.000926)	(0.00120)	(0.00129)	(0.00108)	(0.00117)	(0.00152)	(5.74e-05)
d_remit	-0.789***	-0.511***	-0.376***	-0.311***	-0.586***	-0.399***	-0.339***	-0.277***	0.0228***
	(0.00464)	(0.00407)	(0.00421)	(0.00538)	(0.00585)	(0.00490)	(0.00528)	(0.00689)	(0.000260)
d_occupancy_st	-0.129***	-0.140***	-0.137***	-0.150***	-0.111***	-0.128***	-0.150***	-0.150***	-0.000903***
	(0.00477)	(0.00415)	(0.00424)	(0.00536)	(0.00593)	(0.00497)	(0.00535)	(0.00698)	(0.000263)
d_rentY	-0.0825***	-0.0365***	-0.0246***	0.0175***	-0.0912***	-0.0557***	-0.0436***	0.0272***	0.00441***
	(0.00602)	(0.00523)	(0.00535)	(0.00677)	(0.00748)	(0.00626)	(0.00674)	(0.00880)	(0.000332)
d_shh	-0.00644	0.0317***	0.0601***	0.108***	-0.0431***	0.0192	0.0661***	0.112***	0.00955***
	(0.0130)	(0.0113)	(0.0116)	(0.0148)	(0.0163)	(0.0136)	(0.0147)	(0.0191)	(0.000722)
P_tech_train	0.101***	0.0948***	0.0988***	0.120***	0.200***	0.176***	0.155***	0.152***	-0.00112
	(0.0177)	(0.0156)	(0.0163)	(0.0211)	(0.0225)	(0.0189)	(0.0203)	(0.0265)	(0.00100)
fe_paricipation	0.000136**	0.000352***	0.000470***	0.000880***	-0.000891***	-0.000459***	0.000268***	0.00173***	8.05e-05***
	(5.39e-05)	(4.81e-05)	(5.01e-05)	(6.51e-05)	(6.94e-05)	(5.81e-05)	(6.26e-05)	(8.17e-05)	(3.08e-06)
d_access_BS	0.225***	0.183***	0.172***	0.134***	0.0638***	0.144***	0.217***	0.303***	0.00661***
	(0.00523)	(0.00453)	(0.00461)	(0.00581)	(0.00647)	(0.00541)	(0.00583)	(0.00761)	(0.000287)
Constant	9.684***	9.874***	10.08***	10.35***	9.757***	9.963***	10.11***	10.01***	0.0216***
	(0.0163)	(0.0141)	(0.0145)	(0.0186)	(0.0202)	(0.0169)	(0.0182)	(0.0238)	(0.000896)
Observations	121,068	121,068	121,068	121,068	121,068	121,068	121,068	121,068	121,068
R-squared					0.201	0.268	0.307	0.299	0.132
RIF					10.378	10.693	10.981	11.34	.03361

Table A3: Average Per Capita Equalized Consumption Regression Results for Pakistan

D V: ln_apcc_eq	**Conditional quantile regression**				**Unconditional quantile regression**				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	0.000158	0.00266	0.00263	0.00181	0.00184	0.00157	-0.000121	0.00474	-1.12e-05
	(0.00191)	(0.00292)	(0.00228)	(0.00348)	(0.00330)	(0.00299)	(0.00322)	(0.00402)	(0.000116)
age_he_hh	0.00830***	0.00701***	0.00450***	0.00253***	0.00275***	0.00451***	0.00716***	0.00896***	9.48e-05***
	(0.000444)	(0.000601)	(0.000390)	(0.000560)	(0.000675)	(0.000611)	(0.000660)	(0.000823)	(2.37e-05)
sq_age_he_hh	-9.84e-05***	-7.83e-05***	-4.51e-05***	-1.45e-05**	-3.42e-05***	-4.87e-05***	-7.58e-05***	-8.66e-05***	-2.84e-07
	(4.40e-06)	(6.37e-06)	(4.61e-06)	(6.60e-06)	(7.68e-06)	(6.95e-06)	(7.50e-06)	(9.36e-06)	(2.70e-07)
d_intt_ssl	-0.00947	0.0559**	0.0805***	0.199***	-0.184***	-0.110***	-0.0362*	0.106***	0.0192***
	(0.0256)	(0.0222)	(0.0297)	(0.0442)	(0.0202)	(0.0183)	(0.0198)	(0.0246)	(0.000711)
yrs_edu_wap	0.0361***	0.0385***	0.0397***	0.0419***	0.0255***	0.0326***	0.0403***	0.0542***	0.000819***
	(0.000473)	(0.000441)	(0.000362)	(0.000509)	(0.000612)	(0.000554)	(0.000598)	(0.000746)	(2.15e-05)
d_highpaid_occ	0.149***	0.147***	0.168***	0.177***	0.0334***	0.0678***	0.133***	0.258***	0.00743***
	(0.0102)	(0.0106)	(0.00772)	(0.0117)	(0.00857)	(0.00776)	(0.00837)	(0.0104)	(0.000301)
d_lowpaid_occ	0.0290***	0.0264***	0.0249***	0.0179***	0.0555***	0.0482***	0.0372***	-0.00456	-0.00205***
	(0.00353)	(0.00362)	(0.00301)	(0.00351)	(0.00422)	(0.00382)	(0.00412)	(0.00514)	(0.000148)
d_pub_ass	-0.0553***	-0.0805***	-0.0957***	-0.0996***	-0.132***	-0.138***	-0.113***	-0.0359***	0.00290***
	(0.00388)	(0.00334)	(0.00261)	(0.00348)	(0.00525)	(0.00476)	(0.00513)	(0.00640)	(0.000185)
s_asset	0.0392***	0.0353***	0.0345***	0.0299***	0.0533***	0.0480***	0.0420***	0.0218***	-0.00129***
	(0.000723)	(0.000567)	(0.000630)	(0.000666)	(0.000865)	(0.000784)	(0.000846)	(0.00106)	(3.04e-05)
l_asset	0.0588***	0.0685***	0.0748***	0.0852***	0.0284***	0.0438***	0.0686***	0.107***	0.00274***
	(0.000958)	(0.000694)	(0.000594)	(0.00109)	(0.00101)	(0.000912)	(0.000985)	(0.00123)	(3.54e-05)
d_remit	-0.0100***	-0.0138***	-0.00602**	0.00486	-0.000110	-0.0142***	0.0126***	0.0176***	-0.000205
	(0.00333)	(0.00428)	(0.00265)	(0.00478)	(0.00456)	(0.00413)	(0.00446)	(0.00556)	(0.000161)
d_occupancy_st	-0.154***	-0.172***	-0.186***	-0.205***	-0.100***	-0.161***	-0.192***	-0.252***	-0.00377***
	(0.00396)	(0.00389)	(0.00420)	(0.00480)	(0.00462)	(0.00419)	(0.00452)	(0.00564)	(0.000163)
d_rentY	0.0348***	0.0478***	0.0670***	0.0683***	0.00197	0.0229***	0.0771***	0.106***	0.00235***
	(0.00559)	(0.00496)	(0.00482)	(0.00756)	(0.00583)	(0.00528)	(0.00570)	(0.00711)	(0.000205)
d_shh	0.0985***	0.131***	0.136***	0.145***	0.0766***	0.112***	0.151***	0.159***	0.00337***
	(0.0181)	(0.0122)	(0.0132)	(0.0109)	(0.0127)	(0.0115)	(0.0124)	(0.0155)	(0.000446)
P_tech_train	0.116***	0.0790***	0.100***	0.0864***	0.101***	0.158***	0.128***	0.165***	0.000524
	(0.0204)	(0.0123)	(0.0152)	(0.0194)	(0.0176)	(0.0159)	(0.0172)	(0.0214)	(0.000618)
fe_paricipation	-0.000642***	-0.000534***	-0.000491***	-0.000249***	-0.00165***	-0.00123***	-0.000497***	0.000537***	6.24e-05***
	(4.42e-05)	(4.27e-05)	(4.83e-05)	(4.68e-05)	(5.41e-05)	(4.90e-05)	(5.29e-05)	(6.60e-05)	(1.90e-06)
d_access_BS	0.269***	0.250***	0.226***	0.209***	0.0789***	0.156***	0.266***	0.377***	0.00874***
	(0.00333)	(0.00385)	(0.00339)	(0.00484)	(0.00504)	(0.00456)	(0.00492)	(0.00614)	(0.000177)
Constant	9.785***	9.995***	10.20***	10.43***	9.882***	10.05***	10.12***	10.26***	0.0153***
	(0.0116)	(0.0151)	(0.00964)	(0.0143)	(0.0157)	(0.0142)	(0.0154)	(0.0192)	(0.000553)
Observations	121,058	121,058	121,058	121,058	121,058	121,058	121,058	121,058	121,058
R-squared					0.180	0.271	0.323	0.320	0.152
RIF					10.451	10.706	10.949	11.259	.02596

Table A4: Average Per Capita Equalized Income Regression Results for KPK

D V: ln_apcy_eq	Conditional quantile regression				Unconditional quantile regression				
VARIABLES	**q20**	**q40**	**q60**	**q80**	**q20**	**q40**	**q60**	**q80**	**Gini**
Gender	0.0147	0.0105	0.0143*	0.00791	0.00584	0.0133	0.0208**	0.0177*	-0.000528
	(0.00980)	(0.00945)	(0.00751)	(0.00787)	(0.0119)	(0.00867)	(0.00890)	(0.0103)	(0.000464)
age_he_hh	0.0226***	0.0151***	0.0168***	0.00746***	0.0303***	0.0175***	0.00293*	0.00530***	-0.000805***
	(0.00190)	(0.00162)	(0.00113)	(0.00259)	(0.00231)	(0.00168)	(0.00172)	(0.00200)	(8.98e-05)
sq_age_he_hh	-0.000214***	-0.000132***	-0.000159***	-5.48e-05*	-0.000323***	-0.000176***	-1.31e-06	-1.00e-05	9.44e-06***
	(2.27e-05)	(1.61e-05)	(1.22e-05)	(3.17e-05)	(2.64e-05)	(1.92e-05)	(1.97e-05)	(2.28e-05)	(1.03e-06)
d_intt_ssl	0.134***	-0.106***	-0.297**	-0.150	0.374**	-0.256**	-0.283***	0.152	-0.00947*
	(0.0112)	(0.0204)	(0.127)	(0.103)	(0.147)	(0.107)	(0.109)	(0.127)	(0.00571)
yrs_edu_wap	0.0474***	0.0460***	0.0505***	0.0495***	0.0287***	0.0370***	0.0559***	0.0725***	0.000650***
	(0.00252)	(0.00146)	(0.00106)	(0.00179)	(0.00216)	(0.00157)	(0.00161)	(0.00187)	(8.40e-05)
d_highpaid_occ	0.250***	0.297***	0.237***	0.305***	0.133***	0.155***	0.242***	0.404***	0.0101***
	(0.0201)	(0.0139)	(0.0158)	(0.0228)	(0.0308)	(0.0224)	(0.0230)	(0.0266)	(0.00120)
d_lowpaid_occ	0.0464***	0.0495***	0.0338***	0.0500***	0.108***	0.0920***	0.0732***	0.00680	-0.00274***
	(0.0165)	(0.0108)	(0.0116)	(0.0143)	(0.0166)	(0.0121)	(0.0124)	(0.0144)	(0.000647)
d_pub_ass	-0.129***	-0.109***	-0.125***	-0.140***	-0.153***	-0.170***	-0.152***	-0.0917***	0.00261***
	(0.00964)	(0.0106)	(0.0100)	(0.0104)	(0.0150)	(0.0109)	(0.0112)	(0.0130)	(0.000584)
s_asset	0.0636***	0.0607***	0.0619***	0.0602***	0.0705***	0.0649***	0.0719***	0.0595***	-0.000606***
	(0.00256)	(0.00181)	(0.00201)	(0.00231)	(0.00324)	(0.00236)	(0.00242)	(0.00280)	(0.000126)
l_asset	0.0416***	0.0550***	0.0654***	0.0711***	0.0144***	0.0383***	0.0617***	0.0914***	0.00236***
	(0.00312)	(0.00253)	(0.00233)	(0.00289)	(0.00323)	(0.00235)	(0.00241)	(0.00279)	(0.000126)
d_remit	-0.846***	-0.541***	-0.423***	-0.334***	-0.751***	-0.479***	-0.427***	-0.287***	0.0213***
	(0.0150)	(0.0140)	(0.0134)	(0.0106)	(0.0130)	(0.00945)	(0.00969)	(0.0112)	(0.000505)
d_occupancy_st	-0.118***	-0.124***	-0.114***	-0.131***	-0.107***	-0.120***	-0.163***	-0.134***	-0.000495
	(0.0146)	(0.00925)	(0.0111)	(0.0102)	(0.0157)	(0.0114)	(0.0117)	(0.0136)	(0.000611)
d_rentY	-0.0522**	0.0182*	-0.00120	0.0498***	0.0186	-0.0368***	-0.0501***	0.0214	0.00326***
	(0.0229)	(0.00978)	(0.0131)	(0.0182)	(0.0171)	(0.0125)	(0.0128)	(0.0148)	(0.000667)
d_shh	-0.0868	-0.0868*	-0.0630	-0.00135	-0.221***	-0.0715*	0.00833	0.0834*	0.0146***
	(0.0617)	(0.0472)	(0.0407)	(0.0471)	(0.0508)	(0.0370)	(0.0379)	(0.0439)	(0.00198)
P_tech_train	0.426***	0.248***	0.203***	0.182***	0.494***	0.433***	0.145***	0.373***	-0.00237
	(0.0292)	(0.0265)	(0.0445)	(0.0562)	(0.0674)	(0.0491)	(0.0503)	(0.0583)	(0.00262)
fe_paricipation	0.00150***	0.00154***	0.00190***	0.00195***	0.000400	0.000902***	0.00114***	0.00241***	0.000113***
	(0.000133)	(0.000208)	(0.000188)	(0.000132)	(0.000255)	(0.000186)	(0.000191)	(0.000221)	(9.94e-06)
d_access_BS	0.222***	0.191***	0.172***	0.186***	0.0201	0.117***	0.111***	0.250***	0.0133***
	(0.0168)	(0.0139)	(0.0253)	(0.0464)	(0.0314)	(0.0229)	(0.0234)	(0.0272)	(0.00122)
Constant	9.104***	9.510***	9.624***	10.07***	9.112***	9.540***	9.866***	9.900***	0.0367***
	(0.0524)	(0.0468)	(0.0277)	(0.0418)	(0.0538)	(0.0392)	(0.0402)	(0.0465)	(0.00209)
Observations	26,650	26,650	26,650	26,650	26,650	26,650	26,650	26,650	26,650
R-squared					0.194	0.249	0.292	0.282	0.110
RIF					10.197	10.548	10.858	11.23	.03797

Table A5: Average Per Capita Equalized Consumption Regression Results for KPK

DV: ln_apcc_eq	**Conditional quantile regression**				**Unconditional quantile regression**				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	0.00210	0.00405	0.0112**	0.00872	0.00370	0.00488	0.00571	0.0131	0.000223
	(0.00413)	(0.00368)	(0.00564)	(0.00712)	(0.00616)	(0.00617)	(0.00702)	(0.00883)	(0.000235)
age_he_hh	0.00909***	0.00665***	0.00430***	0.00433**	0.00572***	0.00352***	0.00276**	0.00961***	8.43e-06
	(0.00132)	(0.00117)	(0.000980)	(0.00179)	(0.00119)	(0.00119)	(0.00136)	(0.00171)	(4.55e-05)
sq_age_he_hh	-8.86e-05***	-5.87e-05***	-2.74e-05**	-2.56e-05	-5.69e-05***	-3.08e-05**	-2.29e-05	-5.82e-05***	8.82e-07*
	(1.67e-05)	(1.43e-05)	(1.09e-05)	(2.09e-05)	(1.36e-05)	(1.37e-05)	(1.55e-05)	(1.96e-05)	(5.20e-07)
d_intt_ssl	-0.0640***	-0.240***	-0.156***	-0.343***	-0.0905	-0.195**	-0.196**	-0.411***	-0.00743**
	(0.0210)	(0.0843)	(0.00822)	(0.0269)	(0.0758)	(0.0759)	(0.0864)	(0.109)	(0.00289)
yrs_edu_wap	0.0318***	0.0379***	0.0383***	0.0370***	0.0218***	0.0296***	0.0385***	0.0488***	0.000684***
	(0.000978)	(0.00103)	(0.00115)	(0.00139)	(0.00112)	(0.00112)	(0.00127)	(0.00160)	(4.25e-05)
d_highpaid_occ	0.0998***	0.122***	0.158***	0.157***	0.0209	0.0500***	0.0994***	0.251***	0.00634***
	(0.0159)	(0.0172)	(0.0170)	(0.0185)	(0.0159)	(0.0159)	(0.0181)	(0.0228)	(0.000607)
d_lowpaid_occ	0.00808	0.0209***	0.0215***	0.0127	0.0317***	0.0424***	0.0242**	-0.0232*	-0.00157***
	(0.00695)	(0.00794)	(0.00783)	(0.00909)	(0.00860)	(0.00861)	(0.00980)	(0.0123)	(0.000328)
d_pub_ass	-0.0503***	-0.0874***	-0.108***	-0.0947***	-0.108***	-0.110***	-0.0987***	-0.0777***	0.00124***
	(0.00742)	(0.00478)	(0.00663)	(0.0101)	(0.00775)	(0.00776)	(0.00883)	(0.0111)	(0.000296)
s_asset	0.0589***	0.0592***	0.0590***	0.0620***	0.0555***	0.0642***	0.0748***	0.0627***	-0.000125*
	(0.00107)	(0.00121)	(0.00168)	(0.00225)	(0.00168)	(0.00168)	(0.00191)	(0.00240)	(6.39e-05)
l_asset	0.0290***	0.0339***	0.0457***	0.0604***	0.0141***	0.0241***	0.0491***	0.0756***	0.00185***
	(0.00152)	(0.00166)	(0.00168)	(0.00238)	(0.00167)	(0.00167)	(0.00190)	(0.00240)	(6.37e-05)
d_remit	0.0296***	-0.00592	-0.00296	-0.00500	0.0145**	-0.00218	-0.00619	0.0369***	-0.000349
	(0.00512)	(0.00653)	(0.00534)	(0.0111)	(0.00671)	(0.00672)	(0.00764)	(0.00962)	(0.000256)
d_occupancy_st	-0.125***	-0.150***	-0.152***	-0.152***	-0.0381***	-0.126***	-0.214***	-0.209***	-0.00451***
	(0.00675)	(0.00720)	(0.00782)	(0.0120)	(0.00811)	(0.00812)	(0.00924)	(0.0116)	(0.000309)
d_rentY	0.0540***	0.0648***	0.0407***	0.0634***	0.000222	0.0478***	0.0649***	0.0325**	0.00124***
	(0.0114)	(0.0100)	(0.00805)	(0.0146)	(0.00885)	(0.00886)	(0.0101)	(0.0127)	(0.000338)
d_shh	0.103***	0.163***	0.190***	0.201***	0.0926***	0.112***	0.195***	0.216***	0.00445***
	(0.0216)	(0.0361)	(0.0198)	(0.0275)	(0.0263)	(0.0263)	(0.0299)	(0.0377)	(0.00100)
P_tech_train	0.152***	0.202***	0.271***	0.219***	0.160***	0.135***	0.205***	0.290***	0.00843***
	(0.0238)	(0.0590)	(0.0621)	(0.0393)	(0.0348)	(0.0349)	(0.0397)	(0.0499)	(0.00133)
fe_paricipation	0.00118***	0.00116***	0.000812***	0.00107***	0.000775***	0.000344***	0.000418***	0.00155***	2.08e-05***
	(8.92e-05)	(0.000137)	(0.000160)	(0.000114)	(0.000132)	(0.000132)	(0.000150)	(0.000189)	(5.03e-06)
d_access_BS	0.247***	0.245***	0.231***	0.214***	0.0517***	0.0847***	0.162***	0.483***	0.0126***
	(0.0157)	(0.0193)	(0.0156)	(0.0285)	(0.0162)	(0.0163)	(0.0185)	(0.0233)	(0.000619)
Constant	9.630***	9.833***	10.03***	10.18***	9.743***	9.919***	10.01***	9.971***	0.0141***
	(0.0261)	(0.0282)	(0.0243)	(0.0448)	(0.0278)	(0.0278)	(0.0317)	(0.0399)	(0.00106)
Observations	26,650	26,650	26,650	26,650	26,650	26,650	26,650	26,650	26,650
R-squared					0.138	0.207	0.272	0.270	0.122
RIF					10.417	10.631	10.86	11.171	0.02437

Table A6: Average Per Capita Equalized Income Regression Results for Punjab

DV: ln_apcy_eq	**Conditional quantile regression**				**Unconditional quantile regression**				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	0.00239	0.00309	-0.00153	-0.00622	0.00321	-0.00173	-0.000637	0.0102	4.51e-06
	(0.00538)	(0.00401)	(0.00415)	(0.00387)	(0.00674)	(0.00569)	(0.00575)	(0.00773)	(0.000293)
age_he_hh	0.0101***	0.00575***	0.00547***	-0.000415	0.00666***	0.00727***	0.00406***	0.0103***	-8.69e-05
	(0.00135)	(0.000999)	(0.00109)	(0.00127)	(0.00135)	(0.00114)	(0.00115)	(0.00154)	(5.84e-05)
sq_age_he_hh	-0.000116***	-5.58e-05***	-3.77e-05***	4.33e-05***	-7.57e-05***	-7.27e-05***	-2.26e-05*	-8.23e-05***	1.85e-06***
	(1.55e-05)	(1.15e-05)	(1.30e-05)	(1.43e-05)	(1.50e-05)	(1.27e-05)	(1.28e-05)	(1.72e-05)	(6.53e-07)
d_intt_ssl	0.522***	0.457***	0.526***	0.599***	-0.0436	0.108***	0.272***	0.715***	0.0347***
	(0.0128)	(0.0443)	(0.0305)	(0.0463)	(0.0323)	(0.0273)	(0.0276)	(0.0370)	(0.00140)
yrs_edu_wap	0.0379***	0.0409***	0.0445***	0.0480***	0.0236***	0.0301***	0.0441***	0.0736***	0.00110***
	(0.00182)	(0.00142)	(0.00124)	(0.00142)	(0.00135)	(0.00114)	(0.00115)	(0.00155)	(5.88e-05)
d_highpaid_occ	0.209***	0.225***	0.266***	0.284***	0.0680***	0.123***	0.208***	0.378***	0.00985***
	(0.0213)	(0.0188)	(0.0185)	(0.0246)	(0.0174)	(0.0147)	(0.0149)	(0.0200)	(0.000757)
d_lowpaid_occ	0.0733***	0.0688***	0.0802***	0.0820***	0.116***	0.113***	0.101***	0.0575***	-0.00347***
	(0.00589)	(0.00538)	(0.00637)	(0.00673)	(0.00838)	(0.00707)	(0.00715)	(0.00961)	(0.000364)
d_pub_ass	-0.0903***	-0.163***	-0.208***	-0.294***	-0.484***	-0.309***	-0.130***	0.0119	0.00893***
	(0.0153)	(0.0123)	(0.0110)	(0.0114)	(0.0162)	(0.0137)	(0.0138)	(0.0186)	(0.000704)
s_asset	0.0430***	0.0433***	0.0398***	0.0388***	0.0727***	0.0612***	0.0431***	0.0172***	-0.00168***
	(0.00117)	(0.00142)	(0.00162)	(0.00205)	(0.00186)	(0.00157)	(0.00159)	(0.00213)	(8.07e-05)
l_asset	0.0945***	0.0995***	0.104***	0.108***	0.0458***	0.0670***	0.0858***	0.140***	0.00277***
	(0.00250)	(0.00202)	(0.00228)	(0.00177)	(0.00211)	(0.00178)	(0.00180)	(0.00243)	(9.18e-05)
d_remit	-0.702***	-0.470***	-0.350***	-0.296***	-0.547***	-0.368***	-0.318***	-0.288***	0.0200***
	(0.0135)	(0.0127)	(0.00863)	(0.00826)	(0.00854)	(0.00721)	(0.00729)	(0.00980)	(0.000371)
d_occupancy_st	-0.172***	-0.199***	-0.175***	-0.189***	-0.143***	-0.197***	-0.190***	-0.184***	0.000286
	(0.00877)	(0.00794)	(0.00728)	(0.00794)	(0.00974)	(0.00822)	(0.00831)	(0.0112)	(0.000423)
d_rentY	-0.0709***	-0.0586***	-0.0388***	0.00289	-0.0934***	-0.0555***	-0.0456***	0.0459***	0.00415***
	(0.0119)	(0.00967)	(0.0103)	(0.0163)	(0.0112)	(0.00949)	(0.00959)	(0.0129)	(0.000488)
d_shh	-0.0428	0.0250	0.0638**	0.0989***	-0.0520**	0.0346*	0.0779***	0.0790***	0.00969***
	(0.0303)	(0.0272)	(0.0299)	(0.0158)	(0.0223)	(0.0188)	(0.0191)	(0.0256)	(0.000970)
P_tech_train	0.0250	0.00455	0.0149	0.133***	0.0951***	0.125***	0.0795***	0.116***	0.00132
	(0.0253)	(0.0184)	(0.0291)	(0.0340)	(0.0347)	(0.0293)	(0.0296)	(0.0398)	(0.00151)
fe_paricipation	-0.000672***	0.000104	0.000300***	0.000809***	-0.00147***	-0.000980***	-2.27e-05	0.00176***	0.000103***
	(0.000136)	(6.75e-05)	(5.79e-05)	(6.80e-05)	(0.000106)	(8.96e-05)	(9.06e-05)	(0.000122)	(4.61e-06)
d_access_BS	0.161***	0.134***	0.133***	0.0991***	0.0287***	0.109***	0.154***	0.257***	0.00612***
	(0.00877)	(0.00709)	(0.00866)	(0.0104)	(0.00985)	(0.00832)	(0.00840)	(0.0113)	(0.000428)
Constant	9.658***	9.931***	10.07***	10.39***	9.708***	9.942***	10.17***	10.05***	0.0194***
	(0.0362)	(0.0265)	(0.0296)	(0.0286)	(0.0324)	(0.0273)	(0.0276)	(0.0371)	(0.00140)
Observations	54,478	54,478	54,478	54,478	54,478	54,478	54,478	54,478	54,478
R-squared					0.215	0.275	0.291	0.296	0.129
RIF					10.44	10.77	11.07	11.44	.03482

Table A7: Average Per Capita Equalized Consumption Regression Results for Punjab

DV: ln_apcc_eq	Conditional quantile regression				Unconditional quantile regression				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	-0.000639	-0.00105	-0.000998	-0.00510	-0.00661	-0.00366	-0.00337	-5.20e-05	0.000161
	(0.00341)	(0.00384)	(0.00430)	(0.00497)	(0.00532)	(0.00483)	(0.00484)	(0.00614)	(0.000176)
age_he_hh	0.0122***	0.00972***	0.00726***	0.00575***	0.00735***	0.00977***	0.00951***	0.00970***	0.000148***
	(0.000882)	(0.00110)	(0.000867)	(0.00113)	(0.00106)	(0.000963)	(0.000966)	(0.00122)	(3.51e-05)
sq_age_he_hh	-0.000145***	-0.000118***	-8.41e-05***	-5.35e-05***	-0.000101***	-0.000113***	-0.000105***	-9.93e-05***	-6.60e-07*
	(1.12e-05)	(1.41e-05)	(1.07e-05)	(1.26e-05)	(1.19e-05)	(1.08e-05)	(1.08e-05)	(1.37e-05)	(3.93e-07)
d_intt_ssl	0.00955	0.114***	0.101***	0.237***	-0.0963***	-0.0765***	-0.0746***	0.191***	0.0187***
	(0.0442)	(0.0249)	(0.0292)	(0.0357)	(0.0255)	(0.0231)	(0.0232)	(0.0294)	(0.000843)
yrs_edu_wap	0.0366***	0.0401***	0.0395***	0.0419***	0.0234***	0.0335***	0.0412***	0.0595***	0.000900***
	(0.000783)	(0.000849)	(0.000859)	(0.000937)	(0.00107)	(0.000969)	(0.000972)	(0.00123)	(3.53e-05)
d_highpaid_occ	0.153***	0.138***	0.150***	0.159***	0.0514***	0.0796***	0.130***	0.239***	0.00595***
	(0.00818)	(0.00862)	(0.0110)	(0.0120)	(0.0138)	(0.0125)	(0.0125)	(0.0158)	(0.000455)
d_lowpaid_occ	0.0226***	0.0174***	0.0198***	0.0158**	0.0580***	0.0459***	0.0254***	-0.0157**	-0.00213***
	(0.00503)	(0.00573)	(0.00471)	(0.00630)	(0.00662)	(0.00600)	(0.00602)	(0.00762)	(0.000219)
d_pub_ass	-0.0701***	-0.105***	-0.139***	-0.205***	-0.265***	-0.204***	-0.105***	0.0268*	0.00686***
	(0.00840)	(0.00526)	(0.00663)	(0.0114)	(0.0128)	(0.0116)	(0.0116)	(0.0148)	(0.000423)
s_asset	0.0355***	0.0335***	0.0319***	0.0303***	0.0647***	0.0536***	0.0385***	0.00704***	-0.00184***
	(0.00158)	(0.00127)	(0.000950)	(0.00139)	(0.00147)	(0.00133)	(0.00133)	(0.00169)	(4.85e-05)
l_asset	0.0837***	0.0872***	0.0921***	0.0960***	0.0443***	0.0586***	0.0794***	0.126***	0.00285***
	(0.00242)	(0.00193)	(0.00143)	(0.00212)	(0.00167)	(0.00151)	(0.00152)	(0.00192)	(5.52e-05)
d_remit	0.0234***	0.0401***	0.0452***	0.0414***	0.0812***	0.0651***	0.0389***	0.0282***	-0.00178***
	(0.00696)	(0.00513)	(0.00488)	(0.00453)	(0.00675)	(0.00612)	(0.00614)	(0.00777)	(0.000223)
d_occupancy_st	-0.192***	-0.215***	-0.250***	-0.276***	-0.156***	-0.237***	-0.255***	-0.312***	-0.00349***
	(0.00543)	(0.00446)	(0.00632)	(0.00945)	(0.00769)	(0.00697)	(0.00700)	(0.00886)	(0.000254)
d_rentY	0.0627***	0.0920***	0.0782***	0.0786***	0.0362***	0.0558***	0.113***	0.167***	0.00282***
	(0.00674)	(0.00501)	(0.00884)	(0.00564)	(0.00888)	(0.00805)	(0.00807)	(0.0102)	(0.000293)
d_shh	0.124***	0.141***	0.130***	0.141***	0.0910***	0.134***	0.140***	0.172***	0.00250***
	(0.0257)	(0.0179)	(0.0183)	(0.0226)	(0.0176)	(0.0160)	(0.0160)	(0.0203)	(0.000583)
P_tech_train	0.0256	0.0346**	-0.00160	0.0253	0.0695**	0.0684***	0.0622**	0.107***	0.000993
	(0.0271)	(0.0159)	(0.0266)	(0.0311)	(0.0274)	(0.0248)	(0.0249)	(0.0315)	(0.000905)
fe_paricipation	-0.00126***	-0.00107***	-0.000907***	-0.000465***	-0.00254***	-0.00184***	-0.00104***	0.000433***	8.05e-05***
	(8.88e-05)	(8.16e-05)	(6.78e-05)	(7.89e-05)	(8.38e-05)	(7.60e-05)	(7.62e-05)	(9.66e-05)	(2.77e-06)
d_access_BS	0.212***	0.201***	0.197***	0.180***	0.0498***	0.139***	0.224***	0.323***	0.00747***
	(0.00876)	(0.00753)	(0.00871)	(0.00942)	(0.00778)	(0.00705)	(0.00708)	(0.00896)	(0.000257)
Constant	9.681***	9.922***	10.17***	10.39***	9.731***	9.909***	10.12***	10.31***	0.0170***
	(0.0225)	(0.0221)	(0.0160)	(0.0254)	(0.0255)	(0.0232)	(0.0232)	(0.0294)	(0.000845)
Observations	54,468	54,468	54,468	54,468	54,468	54,468	54,468	54,468	54,468
R-squared					0.232	0.308	0.347	0.342	0.162
RIF					10.466	10.743	11.006	11.332	.02729

Table A8: Average Per Capita Equalized Income Regression Results for Sindh

DV: ln_apcy_eq	**Conditional quantile regression**				**Unconditional quantile regression**				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	0.00982	0.0109*	0.00509	-0.000178	0.00633	0.00556	0.00505	0.0158*	-0.000144
	(0.00653)	(0.00602)	(0.00533)	(0.00677)	(0.00778)	(0.00675)	(0.00718)	(0.00960)	(0.000288)
age_he_hh	-0.00498***	-0.00796***	-0.00412***	-0.00135	-0.0106***	-0.00967***	-0.00234	0.00391*	0.000357***
	(0.00187)	(0.00180)	(0.00133)	(0.00177)	(0.00172)	(0.00149)	(0.00159)	(0.00212)	(6.37e-05)
sq_age_he_hh	6.00e-05***	0.000109***	7.11e-05***	5.04e-05***	0.000130***	0.000114***	4.76e-05***	6.28e-06	-3.38e-06***
	(2.20e-05)	(2.25e-05)	(1.48e-05)	(1.91e-05)	(2.00e-05)	(1.73e-05)	(1.84e-05)	(2.46e-05)	(7.41e-07)
d_intt_ssl	0.162**	0.143***	0.0843	0.216***	0.114*	-0.203***	-0.191***	0.238***	0.0171***
	(0.0722)	(0.0458)	(0.0945)	(0.0807)	(0.0657)	(0.0570)	(0.0607)	(0.0811)	(0.00244)
yrs_edu_wap	0.0268***	0.0344***	0.0406***	0.0491***	0.0103***	0.0280***	0.0433***	0.0707***	0.00146***
	(0.000696)	(0.00126)	(0.000722)	(0.00109)	(0.00145)	(0.00126)	(0.00134)	(0.00179)	(5.39e-05)
d_highpaid_occ	0.217***	0.206***	0.238***	0.293***	0.0424**	0.0752***	0.170***	0.385***	0.0129***
	(0.0208)	(0.0132)	(0.0144)	(0.0254)	(0.0201)	(0.0174)	(0.0185)	(0.0248)	(0.000744)
d_lowpaid_occ	0.0340***	0.0367***	0.0279***	0.0330***	0.0794***	0.0768***	0.0596***	0.00230	-0.00293***
	(0.00893)	(0.00745)	(0.00710)	(0.00889)	(0.00964)	(0.00836)	(0.00890)	(0.0119)	(0.000357)
d_pub_ass	-0.0758***	-0.0687***	-0.0820***	-0.0903***	-0.106***	-0.0894***	-0.110***	-0.0689***	0.00181***
	(0.00862)	(0.0111)	(0.00762)	(0.0110)	(0.0105)	(0.00913)	(0.00972)	(0.0130)	(0.000390)
s_asset	0.0415***	0.0383***	0.0343***	0.0221***	0.0770***	0.0640***	0.0443***	0.00114	-0.00222***
	(0.00131)	(0.00233)	(0.00162)	(0.00223)	(0.00230)	(0.00199)	(0.00212)	(0.00283)	(8.52e-05)
l_asset	0.102***	0.101***	0.0995***	0.112***	0.0491***	0.0639***	0.0961***	0.159***	0.00334***
	(0.00213)	(0.00268)	(0.00169)	(0.00239)	(0.00255)	(0.00221)	(0.00236)	(0.00315)	(9.46e-05)
d_remit	-0.301***	-0.197***	-0.187***	-0.145***	-0.175***	-0.248***	-0.205***	-0.176***	0.00221**
	(0.0484)	(0.0290)	(0.0417)	(0.0272)	(0.0284)	(0.0247)	(0.0263)	(0.0351)	(0.00105)
d_occupancy_st	-0.144***	-0.152***	-0.142***	-0.146***	-0.125***	-0.160***	-0.146***	-0.119***	-0.000667*
	(0.00715)	(0.00799)	(0.00843)	(0.0122)	(0.0109)	(0.00947)	(0.0101)	(0.0135)	(0.000405)
d_rentY	-0.151***	-0.0332	0.0162	0.00824	-0.105***	-0.0569***	0.0146	-0.00209	0.00320***
	(0.0168)	(0.0211)	(0.0211)	(0.0169)	(0.0196)	(0.0170)	(0.0181)	(0.0241)	(0.000725)
d_shh	0.0678*	0.0713***	0.138***	0.128***	0.0238	0.0511*	0.0989***	0.123***	0.00537***
	(0.0361)	(0.0268)	(0.0402)	(0.0325)	(0.0346)	(0.0300)	(0.0320)	(0.0427)	(0.00128)
P_tech_train	0.104***	0.126**	0.0876***	0.110***	0.249***	0.168***	0.202***	0.121**	-0.00254*
	(0.0341)	(0.0495)	(0.0339)	(0.0294)	(0.0405)	(0.0351)	(0.0374)	(0.0500)	(0.00150)
fe_paricipation	-0.000356***	-0.000589***	-0.000706***	-0.000226**	-0.00179***	-0.00127***	-0.000679***	0.000379**	5.17e-05***
	(0.000122)	(0.000122)	(9.24e-05)	(0.000104)	(0.000119)	(0.000104)	(0.000110)	(0.000147)	(4.43e-06)
d_access_BS	0.177***	0.146***	0.149***	0.108***	0.0409***	0.152***	0.213***	0.272***	0.00468***
	(0.00660)	(0.00779)	(0.00456)	(0.00831)	(0.0103)	(0.00894)	(0.00951)	(0.0127)	(0.000382)
Constant	10.06***	10.27***	10.32***	10.43***	10.16***	10.30***	10.23***	10.12***	0.00806***
	(0.0329)	(0.0317)	(0.0298)	(0.0374)	(0.0385)	(0.0334)	(0.0356)	(0.0475)	(0.00143)
Observations	28,316	28,316	28,316	28,316	28,316	28,316	28,316	28,316	28,316
R-squared					0.325	0.371	0.347	0.138	0.216
RIF					10.422	10.708	10.978	11.313	.02923

Table A9: Average Per Capita Equalized Consumption Regression Results for Sindh

DV: ln_apcc_eq	Conditional Quantile regression				Unconditional Quantile regression				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	0.0152***	0.00758	0.00900*	0.00364	0.00857	0.00729	0.00618	0.0154**	-0.000267
	(0.00570)	(0.00468)	(0.00480)	(0.00789)	(0.00701)	(0.00591)	(0.00604)	(0.00756)	(0.000242)
age_he_hh	0.000711	-0.00267**	-0.00107	-0.00125	-0.00296*	-0.00436***	0.00561***	0.00369**	0.000303***
	(0.00162)	(0.00112)	(0.00120)	(0.00109)	(0.00155)	(0.00130)	(0.00133)	(0.00167)	(5.35e-05)
sq_age_he_hh	-2.50e-06	3.29e-05**	2.17e-05	1.97e-05*	4.36e-05**	5.54e-05***	-5.29e-05***	-3.49e-05*	-3.09e-06***
	(1.87e-05)	(1.44e-05)	(1.38e-05)	(1.19e-05)	(1.80e-05)	(1.52e-05)	(1.55e-05)	(1.94e-05)	(6.21e-07)
d_intt_ssl	-0.0577***	-0.0407	0.00417	0.0968	-0.399***	-0.167***	-0.164***	0.0446	0.0179***
	(0.0173)	(0.0620)	(0.0909)	(0.115)	(0.0593)	(0.0499)	(0.0510)	(0.0639)	(0.00205)
yrs_edu_wap	0.0279***	0.0296***	0.0369***	0.0373***	0.0132***	0.0240***	0.0344***	0.0531***	0.00122***
	(0.000981)	(0.000966)	(0.00133)	(0.00142)	(0.00131)	(0.00110)	(0.00113)	(0.00141)	(4.52e-05)
d_highpaid_occ	0.166***	0.176***	0.176***	0.215***	0.0131	0.0627***	0.123***	0.266***	0.0105***
	(0.0150)	(0.0107)	(0.0172)	(0.0313)	(0.0181)	(0.0152)	(0.0156)	(0.0195)	(0.000624)
d_lowpaid_occ	0.00810	0.0158**	0.0144*	0.00718	0.0591***	0.0365***	0.0273***	-0.00847	-0.00251***
	(0.00594)	(0.00683)	(0.00762)	(0.00810)	(0.00869)	(0.00732)	(0.00748)	(0.00936)	(0.000300)
d_pub_ass	-0.0709***	-0.0660***	-0.0610***	-0.0793***	-0.0852***	-0.122***	-0.108***	-0.0548***	0.00204***
	(0.00619)	(0.00486)	(0.00715)	(0.00925)	(0.00949)	(0.00799)	(0.00818)	(0.0102)	(0.000328)
s_asset	0.0417***	0.0413***	0.0399***	0.0293***	0.0799***	0.0655***	0.0448***	0.00664***	-0.00233***
	(0.00144)	(0.00135)	(0.00183)	(0.00133)	(0.00207)	(0.00174)	(0.00178)	(0.00223)	(7.15e-05)
l_asset	0.0831***	0.0844***	0.0850***	0.0983***	0.0356***	0.0438***	0.0752***	0.123***	0.00341***
	(0.00237)	(0.00256)	(0.00216)	(0.00221)	(0.00230)	(0.00194)	(0.00198)	(0.00248)	(7.94e-05)
d_remit	0.0144	0.00507	0.0416**	0.0924***	0.0654**	0.119***	0.0235	0.0958***	0.00142
	(0.0154)	(0.0202)	(0.0209)	(0.0259)	(0.0256)	(0.0216)	(0.0221)	(0.0276)	(0.000885)
d_occupancy_st	-0.143***	-0.180***	-0.184***	-0.186***	-0.126***	-0.164***	-0.152***	-0.212***	-0.00278***
	(0.00872)	(0.00890)	(0.00920)	(0.0130)	(0.00984)	(0.00829)	(0.00848)	(0.0106)	(0.000340)
d_rentY	0.0849***	0.101***	0.0937***	0.100***	0.0611***	0.0808***	0.0996***	0.103***	-0.00113*
	(0.0114)	(0.0161)	(0.0165)	(0.0218)	(0.0176)	(0.0149)	(0.0152)	(0.0190)	(0.000609)
d_shh	0.102***	0.0933***	0.111***	0.156***	0.0472	0.0614**	0.123***	0.109***	0.00390***
	(0.0367)	(0.0269)	(0.0298)	(0.0265)	(0.0312)	(0.0263)	(0.0269)	(0.0336)	(0.00108)
P_tech_train	0.0796***	0.121***	0.0898***	0.0744	0.215***	0.272***	0.156***	0.108***	-0.00490***
	(0.0150)	(0.0450)	(0.0191)	(0.0669)	(0.0365)	(0.0307)	(0.0314)	(0.0393)	(0.00126)
fe_paricipation	-0.000985***	-0.00134***	-0.00114***	-0.000925***	-0.00233***	-0.00189***	-0.00108***	-0.000456***	5.12e-05***
	(8.21e-05)	(7.50e-05)	(6.73e-05)	(8.45e-05)	(0.000108)	(9.07e-05)	(9.27e-05)	(0.000116)	(3.72e-06)
d_access_BS	0.176***	0.133***	0.136***	0.136***	0.0330***	0.130***	0.209***	0.209***	0.00562***
	(0.0112)	(0.00745)	(0.00633)	(0.0110)	(0.00929)	(0.00782)	(0.00800)	(0.0100)	(0.000321)
Constant	10.03***	10.32***	10.38***	10.60***	10.06***	10.32***	10.25***	10.51***	0.0110***
	(0.0287)	(0.0265)	(0.0262)	(0.0280)	(0.0347)	(0.0293)	(0.0299)	(0.0374)	(0.00120)
Observations	28,316	28,316	28,316	28,316	28,316	28,316	28,316	28,316	28,316
R-squared					0.246	0.355	0.397	0.358	0.168
RIF					10.474	10.738	10.992	11.286	.02622

Table A10: Average Per Capita Equalized Income Regression Results for Balochistan

D V: ln_apcc_eq	**Conditional quantile regression**				**Unconditional quantile regression**				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	-0.00102	-2.76e-09	0.00168	0.00420	0.00789	0.00171	-0.000871	-0.00486	-0.000236
	(0.00588)	(0.00420)	(0.00543)	(0.00660)	(0.0103)	(0.00835)	(0.00994)	(0.0123)	(0.000393)
age_he_hh	0.00357	0.00531**	0.00248	-0.00316	0.00746***	0.00301	0.00305	0.00309	-0.000147
	(0.00257)	(0.00269)	(0.00248)	(0.00253)	(0.00255)	(0.00206)	(0.00246)	(0.00304)	(9.72e-05)
sq_age_he_hh	-2.54e-05	-5.80e-05*	-1.39e-05	4.22e-05	-8.22e-05***	-2.41e-05	-4.20e-05	-1.86e-05	2.85e-06**
	(2.95e-05)	(3.07e-05)	(2.77e-05)	(3.01e-05)	(3.00e-05)	(2.42e-05)	(2.88e-05)	(3.56e-05)	(1.14e-06)
d_intt_ssl	-0.534***	-0.0924***	-0.139***	-0.379	-0.492***	-0.128**	-0.279***	-0.0408	0.0124***
	(0.171)	(0.0318)	(0.0432)	(0.242)	(0.0701)	(0.0567)	(0.0675)	(0.0834)	(0.00267)
yrs_edu_wap	0.0361***	0.0381***	0.0378***	0.0459***	0.0235***	0.0245***	0.0379***	0.0474***	0.00106***
	(0.00195)	(0.00194)	(0.00140)	(0.00240)	(0.00181)	(0.00146)	(0.00174)	(0.00215)	(6.89e-05)
d_highpaid_occ	0.189***	0.254***	0.252***	0.344***	0.0461	0.108***	0.176***	0.368***	0.0136***
	(0.0300)	(0.0306)	(0.0348)	(0.0327)	(0.0286)	(0.0231)	(0.0275)	(0.0340)	(0.00109)
d_lowpaid_occ	0.0330***	0.0349***	0.00784	0.0170	0.0516***	0.0491***	0.0514***	0.000776	-0.00238***
	(0.00854)	(0.0113)	(0.00921)	(0.0143)	(0.0139)	(0.0112)	(0.0133)	(0.0165)	(0.000528)
d_pub_ass	-0.250***	-0.184***	-0.167***	-0.0811***	-0.275***	-0.0961***	-0.173***	-0.150***	0.00262***
	(0.0166)	(0.0136)	(0.0266)	(0.0227)	(0.0198)	(0.0160)	(0.0190)	(0.0235)	(0.000753)
s_asset	0.0522***	0.0530***	0.0492***	0.0369***	0.0569***	0.0499***	0.0463***	0.0399***	0.000368***
	(0.00194)	(0.00232)	(0.00283)	(0.00231)	(0.00294)	(0.00237)	(0.00283)	(0.00349)	(0.000112)
l_asset	0.0535***	0.0622***	0.0670***	0.0823***	0.0354***	0.0446***	0.0698***	0.106***	0.00188***
	(0.00285)	(0.00192)	(0.00287)	(0.00337)	(0.00369)	(0.00298)	(0.00355)	(0.00439)	(0.000141)
d_remit	-0.228***	0.0401	-0.0471	0.0409	-0.217***	-0.114***	0.0470	0.0993*	0.0129***
	(0.0227)	(0.0916)	(0.0300)	(0.0506)	(0.0475)	(0.0384)	(0.0457)	(0.0565)	(0.00181)
d_occupancy_st	-0.0442***	-0.0536***	-0.0711***	-0.0787***	-0.0333**	-0.0590***	-0.0746***	-0.0621***	-0.00265***
	(0.0138)	(0.0126)	(0.0107)	(0.0193)	(0.0156)	(0.0126)	(0.0150)	(0.0186)	(0.000594)
d_rentY	0.0243	0.0520	0.0609***	0.0683	-0.109***	0.000540	0.0769**	0.0871**	0.00481***
	(0.0338)	(0.0415)	(0.0173)	(0.0985)	(0.0321)	(0.0260)	(0.0309)	(0.0382)	(0.00122)
d_shh	0.0343	0.0819**	0.0277	0.0582	0.00828	-0.00144	0.0503	0.144**	0.00221
	(0.0667)	(0.0405)	(0.0600)	(0.0557)	(0.0616)	(0.0497)	(0.0592)	(0.0732)	(0.00234)
P_tech_train	0.119*	-0.0189	0.201***	0.0216	-0.101	-0.0173	0.0618	0.175**	0.000869
	(0.0639)	(0.0368)	(0.0636)	(0.0526)	(0.0628)	(0.0507)	(0.0604)	(0.0746)	(0.00239)
fe_paricipation	0.00150***	0.00136***	0.00164***	0.00235***	-0.000139	-1.59e-05	0.00127***	0.00288***	0.000124***
	(0.000147)	(0.000134)	(0.000205)	(0.000228)	(0.000208)	(0.000168)	(0.000200)	(0.000247)	(7.92e-06)
d_access_BS	0.0517	0.139***	0.128***	0.142***	-0.0765**	0.00529	0.168***	0.325***	0.0124***
	(0.0542)	(0.0386)	(0.0405)	(0.0445)	(0.0309)	(0.0250)	(0.0297)	(0.0367)	(0.00118)
Constant	9.727***	9.854***	10.08***	10.37***	9.753***	10.05***	10.12***	10.17***	0.0129***
	(0.0525)	(0.0582)	(0.0595)	(0.0682)	(0.0561)	(0.0454)	(0.0540)	(0.0667)	(0.00214)
Observations	11,624	11,624	11,624	11,624	11,624	11,624	11,624	11,624	11,624
R-squared					0.154	0.202	0.232	0.247	0.118
RIF					10.42	10.637	10.837	11.114	0.02378

Table A11: Average Per Capita Equalized Consumption Regression Results for Balochistan

D V: apcc_eq	Conditional quantile regression				Unconditional quantile regression				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
VARIABLES	q20	q40	q60	q80	q20	q40	q60	q80	Gini
Gender	-4.36e-09	-1.25e-09	7.11e-09	0.0104	0.0105	0.00631	0.000674	-0.00189	-0.000371
	(0.00627)	(0.00511)	(0.00683)	(0.00760)	(0.00917)	(0.00789)	(0.00740)	(0.0107)	(0.000322)
age_he_hh	0.00484***	0.00331	0.00595**	0.00685***	0.00447**	0.00208	0.00709***	-0.000263	-0.000280***
	(0.00156)	(0.00275)	(0.00284)	(0.00246)	(0.00227)	(0.00195)	(0.00183)	(0.00265)	(7.97e-05)
sq_age_he_hh	-7.00e-05***	-5.59e-05*	-6.85e-05*	-8.21e-05***	-6.36e-05**	-4.32e-05*	-7.27e-05***	-9.81e-06	4.05e-06***
	(1.81e-05)	(3.29e-05)	(3.57e-05)	(2.78e-05)	(2.66e-05)	(2.29e-05)	(2.15e-05)	(3.11e-05)	(9.35e-07)
d_intt_ssl	-0.558***	-0.405***	-0.334***	-0.540***	-0.404***	-0.386***	-0.180***	-0.0347	0.0189***
	(0.00867)	(0.0221)	(0.0980)	(0.126)	(0.0622)	(0.0535)	(0.0502)	(0.0726)	(0.00219)
yrs_edu_wap	0.0260***	0.0259***	0.0233***	0.0303***	0.0167***	0.0199***	0.0223***	0.0354***	0.000523***
	(0.00106)	(0.00125)	(0.00145)	(0.00186)	(0.00161)	(0.00138)	(0.00130)	(0.00188)	(5.65e-05)
d_highpaid_occ	0.0616**	0.111***	0.195***	0.169***	-0.00399	0.0698***	0.0878***	0.216***	0.00774***
	(0.0291)	(0.0236)	(0.0267)	(0.0371)	(0.0254)	(0.0218)	(0.0205)	(0.0296)	(0.000891)
d_lowpaid_occ	0.0436***	0.0248**	0.0251**	0.0140	0.0453***	0.0469***	0.0376***	0.0283**	-0.00108**
	(0.0146)	(0.0121)	(0.0113)	(0.0104)	(0.0123)	(0.0106)	(0.00992)	(0.0144)	(0.000432)
d_pub_ass	-0.0808**	-0.105***	-0.104***	-0.0931***	-0.158***	-0.124***	-0.105***	-0.0725***	6.71e-05
	(0.0386)	(0.0111)	(0.0116)	(0.0139)	(0.0176)	(0.0151)	(0.0142)	(0.0205)	(0.000617)
s_asset	0.0591***	0.0497***	0.0373***	0.0336***	0.0579***	0.0498***	0.0405***	0.0370***	-0.000701***
	(0.00253)	(0.00253)	(0.00209)	(0.00400)	(0.00261)	(0.00224)	(0.00210)	(0.00305)	(9.17e-05)
l_asset	0.0348***	0.0394***	0.0500***	0.0640***	0.0185***	0.0328***	0.0418***	0.0812***	0.00133***
	(0.00372)	(0.00293)	(0.00243)	(0.00359)	(0.00328)	(0.00282)	(0.00264)	(0.00383)	(0.000115)
d_remit	0.315***	0.223***	0.151***	0.0647*	0.230***	0.0338	0.141***	0.413***	0.00263*
	(0.0305)	(0.0275)	(0.00728)	(0.0335)	(0.0422)	(0.0363)	(0.0340)	(0.0492)	(0.00148)
d_occupancy_st	-0.134***	-0.119***	-0.148***	-0.169***	-0.0833***	-0.104***	-0.0891***	-0.157***	-0.00313***
	(0.00950)	(0.0122)	(0.0115)	(0.0132)	(0.0139)	(0.0119)	(0.0112)	(0.0162)	(0.000487)
d_rentY	0.140***	0.0834**	0.0890***	0.0817***	0.104***	0.122***	0.0620***	0.149***	0.00669***
	(0.00813)	(0.0380)	(0.0264)	(0.0231)	(0.0285)	(0.0245)	(0.0230)	(0.0333)	(0.00100)
d_shh	0.153***	0.105***	0.0671	0.108**	0.0634	0.0872*	0.0983**	0.0983	0.00269
	(0.0447)	(0.0271)	(0.0535)	(0.0552)	(0.0546)	(0.0470)	(0.0441)	(0.0638)	(0.00192)
P_tech_train	0.303***	0.143***	0.0785*	0.175***	0.00301	0.0972**	0.0956**	0.256***	0.000731
	(0.109)	(0.0358)	(0.0419)	(0.0447)	(0.0557)	(0.0479)	(0.0449)	(0.0650)	(0.00196)
fe_paricipation	0.00132***	0.000978***	0.000810***	0.000436**	-0.000211	-0.000298*	0.00118***	0.00128***	5.59e-05***
	(0.000165)	(9.91e-05)	(0.000141)	(0.000189)	(0.000185)	(0.000159)	(0.000149)	(0.000216)	(6.49e-06)
d_access_BS	0.0576*	0.134***	0.176***	0.138***	-0.0288	-0.0227	0.107***	0.290***	0.0124***
	(0.0297)	(0.0233)	(0.0433)	(0.0180)	(0.0274)	(0.0236)	(0.0221)	(0.0320)	(0.000963)
Constant	9.927***	10.17***	10.31***	10.43***	9.986***	10.25***	10.22***	10.49***	0.0214***
	(0.0338)	(0.0516)	(0.0529)	(0.0466)	(0.0498)	(0.0428)	(0.0402)	(0.0582)	(0.00175)
Observations	11,624	11,624	11,624	11,624	11,624	11,624	11,624	11,624	11,624
R-squared					0.137	0.190	0.208	0.215	0.077
RIF					10.442	10.652	10.811	11.048	0.02017