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The Construction of an Asset Index at Household Level and Measurement of Economic Disparities in Punjab (Pakistan) by using MICS Micro-Data

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Abstract

The main objectives of this study are to construct a valid and reliable asset index at household level and to estimate economic disparities in 36 districts of Punjab (Pakistan) by using the Multiple Indicators Cluster Survey (MICS) micro-data. An asset index may be a better measure than current income or expenditure for gauging a household's long-term capacity for buying goods and services and its potential resilience to economic shocks. This paper provides details of the results from Exploratory Factor Analysis (EFA) and Tetrachoric Principal Component Analysis (PCA) for the dimensional structure of assets. We have applied Classical Test Theory (CTT) and Item Response Theory (IRT) in order to construct a reliable household level asset index. In Punjab, Lahore has the highest asset index score followed by Gujrat and Sialkot. Gini-coefficient index and the Palma ratio analyses show that the asset distribution in the district of Rajanpur is highly unequal.

Keywords: Asset Index, Classical Test Theory, Item Response Theory, Exploratory Factor Analysis, Gini-coefficient, Palma ratio, Punjab

1. INTRODUCTION

The coexistence of deep and persistent disparities as well as increasing prosperity is a paradox of the 21st century that raised questions to the present processes of modernisation and global development (Unesco, 2016). Sustainable Development Goal (SDG) 10 is devoted to reducing inequalities between and within countries (United Nations, 2015). Disparities may result from natural differences, differences in socio-cultural conditions and differences resulting from policy decisions. In Pakistan, the richest 20% spend seven times more than the poorest 20%. Pakistan is facing severe social, regional and income inequalities and is ranked at 143 out of 144 countries on the Global Gender Gap index (World Economic Forum, 2017). Pakistan consists of four provinces, including Punjab. About 56% of the population of Pakistan live in Punjab and produce 52% of the GDP. Punjab has nine administrative divisions and 36 districts. Punjab's poorest districts are the home of one-fourth of the most deprived population of Pakistan (Naveed et al., 2018).

This research¹ endeavours to construct an asset index at household level to estimate economic disparities by using Multiple Indicators Cluster Survey (MICS) micro-data for Punjab (Pakistan). Income has long been used to measure living standards and economic well-being. However, the quality of income data has been questioned because earnings are often highly variable for people working in informal labour markets or engaged in small businesses (Moser & Felton, 2007). Expenditure measures became popular during the 1990s as proxies for consumption (Ravallion, 1992).

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Economists believe that consumption is less volatile than income because households, in theory, base their consumption on permanent income (long-term income). The Permanent Income Hypothesis (PIH) states that changes in households' consumption patterns are driven by fluctuations in permanent income rather than current income (Freidman, 1957). Permanent income is defined as the expected long-term average income and thus it may be reflected in the quality and quantity of asset ownership of the household. Additionally, if people are asked about their ownership from a list of assets, there are usually only limited measurement problems. Asset ownership may produce a good picture of permanent income as assets are often accumulated over an extended period and provide a measure of multidimensional aspects of household living standards (Adato, Carter & May 2006; Filmer & Pritchett, 2001; Sahn & Strifel, 2003; Howe et al., 2008). Thus, an asset index can be defined as a measure of a household's long-term average income and their standard of living.

In this paper, we draw on measurement theory and the reflective measurement model to select an optimal subset of household assets and construct a valid and reliable asset index for the Punjab (Pakistan) to estimate economic disparities by using MICS microdata. We have measured asset disparities by using Gini-coefficient and Palma Ratio. The rest of this paper is structured as follows. Section 2 reviews relevant literature on construction of asset index and measurement of disparities. Section 3 describes data and methodology, and section 4 presents findings on asset index and asset disparities in Punjab (Pakistan). Section 5 concludes the paper.

2. REVIEW OF THE LITERATURE

2.1 The debate on the construction of asset indices

Although asset and Unmet Basic Needs (UBN) measures have been used extensively in Latin America for decades (Beccaria & Minujin, 1985), during the 21st Century they have received increasing attention from development economists in other regions of the world (Carter & May, 2001). There is an extensive literature on the use of asset indices to study disparities in educational outcomes (e.g., Ainsworth & Filmer, 2006; Bicego et al., 2003), health outcomes (e.g., Bollen et al., 2002; Schellenberg et al., 2003), child malnutrition (Sahn & Strifel, 2003; Tarozzi & Mahajan, 2005) and child mortality (Sastry, 2004; Stewart and Simelane, 2005).

Harttgen and Volmer (2011) have used an asset index as a proxy for per capita income to compare household levels of human development. Some research studies consider an asset index to be a better measure than expenditure data for explaining variations in fertility, nutrition, child health care and education (Filmer & Pritchett, 2001; Bollen et al., 2002; Sahn & Strifel, 2003; Filmer & Scott, 2008).

The ease of computation, the availability of a variety of questions in household surveys regarding asset ownership and higher reliability of data collection compared with data on income or expenditure variables are the some of the reasons for the widespread use of asset indices (Sahn & Strifel, 2003; McKenzie, 2005; Harttgen and Vollmer, 2011; Harttgen and Klasen, 2012; Filmer & Scott, 2008). In short, an asset index can be a better measure than current income or expenditure in gauging the long-term household capacity for buying goods and services and resilience to economic shocks (Filmer & Pritchett, 2001).

The main challenges for asset index construction are the selection and weighting of items to include in the measure. Over the past 25 years measurement theory approaches have been increasingly applied for asset and deprivation indicator selection to help construct standard of living indices – a deprivation or poverty index can be considered to measure a low standard of

living whereas an asset index is a broader measure of living standards (Catalán, 2019; John & Benet-Martínez, 2014). There are two main approaches: formative and reflective. The MPI, for example, is formative and the European measure is an example of reflective. There is some consensus that reflective measurement is better and is more consistent with the scientific method as it works with testable assumptions. The formative framework does not care much about empirical scrutiny (Coltman, Devinney, Midgley, & Venaik, 2008). In the Reflective Measurement Model, the indicators are causally related to the latent variable, i.e., when the latent variable changes (e.g., living standards get better or worse) then the indicators (asset possession) will change (Brown, 2014).

This approach has many useful properties. For example, the indicators are substitutable. It is not necessary to include all possible indicators to achieve a good measure of living standards and you do not need to use an identical set of indicators in each country/context, i.e., one can use the most appropriate set of indicators in each administrative area/country and still achieve a comparable measurement (Gordon & Najera, 2019). Measurement theory also provides a formal framework for assessing the validity (i.e., the amount of systematic error) and the reliability (i.e., the amount of random error) of the asset index and thus helps to identify the optimum sub-set of indicators, i.e., which indicators to keep and which to drop (Rio Group, 2006; Guio, Gordon & Marlier, 2012; 2016; 2017; 2018; McDonald, 2013; Vollmer & Alkire, 2018; Najera & Gordon, 2019).

The easiest method for producing an asset index is to simply add up the assets owned by a household (Jensen, 1996; McKenzie, 2005). However, Filmer & Pritchett (2001) used Principal Component Analysis (PCA) for weighting assets in the construction of an index and many other researchers have adopted their PCA based methodology (Minujin & Bang, 2002; McKenzie, 2005; Vyass & Kumaranayake, 2006; Labonne, Biller & Chase, 2007). PCA is a

multivariate statistical procedure for data reduction which transforms the variables into a smaller number of orthogonal components, where each component is a linearly weighted combination of the primary variables (Vyas & Kumaranayka, 2006). The first (principal) component is chosen for the asset index because it describes the largest amount of the variation in the raw data – typically about 25% to 30% in most countries (Filmer & Pritchett, 2001; Smits & Steendijk, 2015).

PCA has faced severe criticism regarding the weights allocated to each asset, particularly when assets are unequally distributed among the households. Vyas and Kumaranayake (2006) have argued that PCA based asset indices may have problems of clumping, truncation and comparability across time and space. To improve geographic comparability, Smits and Steendijk (2015) calculated an International Wealth Index (IWI) for 97 developing countries using data from 2.1 million households. To test the validity and reliability of IWI, they also repeated their analysis using categorical principal component analysis, Factor Analysis and Multiple Correspondence Analysis. Vollmer and Alkire (2018) adopted the methodological framework developed by the UK Poverty and Social Exclusion projects² (Gordon et al., 2003; Gordon & Townsend, 2000; Guio, Gordon, & Marlier, 2012; Guio et al., 2016) to produce a reliable global multidimensional asset indicator.

The problem with the PCA methodology is that it is both highly data dependant and can produce essentially arbitrary results. The choice of variables in the index may impact on rich-poor differences and can result in geographical bias when infrastructure variables are included (Vyas & Kumaranayake, 2006). Howe and colleagues (2012) discuss two disadvantages in PCA: (a) the first component explains the greatest proportion of variance among the selected variables but, for most of the cases, the first component explains less than 30% of the total

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² See www.poverty.ac.uk.

variance; (b) PCA assumes continuous data for analysis while almost all of asset variables are binary (Falkingham & Namazie, 2002). Therefore, asset index weights generated by PCA on untransformed binary data are of highly questionable validity. PCA can be used with continuous data but, when the data are categorical, then they can be suitably transformed using tetrachoric or polychromic correlation coefficients (Kolenikov & Angeles, 2009). Other, possibly better, methods include non-linear canonical correlation analysis, multiple correspondence analysis and latent trait analysis (Falkenham & Namazie, 2002; Guio, Gordon & Marlier, 2012).

The debate on measurement of asset indices centre on the selection of appropriate assets and the calculation of plausible weights for each item. The simplest methods are to assign equal weights to each asset; weight according to the price value of each asset (Dargent-Molina et al., 1994) or weight by the loading on a latent asset variable but each of these techniques has limitations (Howe et al., 2008; 2012). Assigning differential weights to items in the asset index confers a value judgement that some assets/items are more important measures than others (Ferreira & Lugo, 2013). Researchers often calculate differential weights for asset indices to reflect the differences in standard of living implied by possession (or lack of possession) of each of the items in the index. However, measurement theory demonstrates that a reliable index is self-weighting, i.e., even if it is possible to assign a ‘perfect’ and error free set of differential weights to each item in the asset index, the final result would be effectively identical to the unweighted asset index (Ghiselli, Campbell & Zedek, 1981; Gordon et al., 2012; Catalán, 2019).

Besides the choice of an appropriate method for weighing the assets, the selection of appropriate assets is also a key element for reliable asset index construction. Classical Test Theory (CTT) has been widely used in both the natural and social sciences to estimate the

internal consistency of scales and indices. The value of Cronbach's alpha coefficient is calculated from the number of assets used in the index and their average inter correlation. Item Response Theory (IRT), also known as latent trait analysis, is a set of statistical models that refer to the association between a household's response regarding ownership of an asset and an unobserved latent trait such as living standard or permanent income. This sophisticated technique has been used for poverty and deprivation measurement (see Cappellari & Jenkins, 2007; Fusco & Dickes, 2008; Guio, Gordon & Marlier, 2012). This research has used Exploratory Factor Analysis (EFA) with oblique rotation and Tetrachoric Principal Component Analysis (PCA) to help identify the dimensional structure of items in the asset index and CTT and IRT to calculate the reliability of the asset index. In order to test the construct validity of each item in the asset index, their correlation with a household income measure was calculated (by using information from the MICS survey regarding earnings of every individual from all main and additional sources) – it was assumed *a priori* that possession of an asset should be correlated with a higher current household income.

2.2 A debate on the measurement of disparities

A wide range of approaches exist for the measurement and analysis of disparities (De Maio, 2007). The Lorenz curve is a popular way to represent inequality and the Gini-coefficient index is an extensively cited measure of income inequality. It is based on the Lorenz curve framework and results range between 0 (perfect equality) and 1 (perfect inequality). There are, however, some limitations with the Gini-index, such as decomposability and additivity problems (Bellù & Liberati, 2011).

The Palma Ratio is known for its simplicity of measurement and interpretation. The Palma ratio is the ratio of the top 10% to the bottom 40% of the population. This measure is based on the empirical observations of Jose Gabriel Palma (2011) that changes in income distribution are largely confined to the lowest and highest tails of the distribution, while middle class income remains relatively stable over time and across countries.

To sum up, the Gini-coefficient is the most widely used measure of inequality and the Palma Ratio has been adopted by the UN to monitor inequality for the SDGs, particularly Goal 10.1, which is to, "by 2030, progressively achieve and sustain income growth of the bottom 40 per cent of the population at a rate higher than the national average". The Palma ratio has also been widely used by the UNDP and many other UN organisations and governments. This research study has measured asset disparities by using the Gini-coefficient and Palma Ratio.

3. DATA AND METHODOLOGY

3.1 Data and sampling

This research has used micro-data from the 2014 Punjab MICS collected by the Pakistan Bureau of Statistics in collaboration with UNICEF. This survey was conducted in all nine divisions and 36 districts of Punjab. The achieved sample³ size was 38,405 households (98% response rate).

3.2 Analytical framework

This research adopted a modified version of the analytical framework approved by the European Union for the construction of deprivation indices (Guio, Gordon & Marlier, 2012),

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³ See details on sampling via https://mics-surveys-prod.s3.amazonaws.com/MICS5/South%20Asia/Pakistan%20%28Punjab%29/2014/Final/Pakistan%20%28Punjab%29%202014%20MICS_English.pdf

which stresses the importance assessing the reliability and validity of indices and their individual indicators.

The Classical Test Theory (CTT) framework was used to assess the reliability of the asset scale, to measure the internal consistency of the scale as a whole - i.e., how closely related the set of asset items are as a group. This analysis is based on the Cronbach's Alpha statistic. The reliability analysis of the asset scale as a whole is complemented with additional tests on the reliability of each individual item in the scale using Item Response Theory (IRT). Finally, an Omega Analysis is reported.

The validity of individual asset items was assessed, to ensure that each item exhibits statistically significant difference in equivalised mean household income in an ANOVA analysis. As the asset index can be considered to be a measure of permanent income (i.e., long term average household income) there therefore should be some association between long-term average household incomes and current household incomes – although this correlation may not always be strong (Haider & Solon, 2006; Lusardi, 1996).

The analytical framework used in this research is consistent with internationally recommended best practice for living standards index construction. For example, the World Bank Commission on Global Poverty report recommended (Principal 4) that indicators should be sufficiently robust and statistically validated (World Bank, 2017) and the United Nations Economic Commission for Europe (UNECE) has argued (Recommendation 28) that the validity and reliability of deprivation indicators should be assessed (UNECE, 2020). These recommendations have been formally endorsed by the Conference of European Statisticians (CES), which sets international statistical norms and standards for use in 60 European and other countries.

3.3 Asset Index data

The MICS collects information about four different kinds of assets, including housing conditions, consumer durables, productive durables, and agriculture related assets. Housing is very important to gauge the living standard of a family and is a vital part of permanent income. Housing includes the main construction materials of a dwelling's floor, roof and exterior walls. Quality of housing is derived from the construction material used, either made from natural material, finished material or in between these two extremes. Consumer durables include a television, iron, motorcycle, pump, mobile, watch, fan, bicycle, radio, electricity, phone and gas for cooking. The productive durables include refrigerator, washing machine, sewing machine, air conditioner, car, computer, water filter, cooking range, boat and bus. Moser & Felton (2007) classify these as financial capital assets. The information about assets in the MICS data is limited to binary (yes/no) responses by the household respondent regarding the ownership of 30 assets and does not include any information about the quality of the assets.

3.4 Asset Index construction

In total, 22 assets are included for calculation of the asset index. The formal equation for the asset index is as follows:

$$A^h = \hat{y}_1 a_{i1} + \dots + \hat{y}_n a_{in} \quad \text{Eq (1)}$$

Here, A^h refers to the household specific asset index and $\hat{y}$ refers to particular weights for each individual asset owned by the household. As the asset index was found to be highly reliable each item was assigned an equal weight. The a_{in} is the respective asset of i^{th} household recorded as a dichotomous variable in Punjab MICS 2014 data sets.

In the second step, the household specific asset index is normalized using following formula,

$$Y^h = \frac{A^h - (\min A^h)}{\text{Max } A^h - (\min A^h)} \quad h = 1, 2, \dots, K \quad \text{Eq (2)}$$

where Y^h is the normalised asset index and A^h is the household specific asset index under study.

3.5 Measurement of disparities: Gini-coefficient and Palma Ratio

The most appealing property of the Lorenz curve framework is that it could generate a single summary statistic of the distribution, known as Gini-coefficient. It is measured by dividing the size of the area between the Lorenz curve and 45-degree perfect equality line by the total area under the perfect equality line. The value of Gini-coefficient lies between 0 and 1. Where 0 mean perfect equality that reflects the equal distribution of income share among all people of the society. The Palma, also known as inter-decile ratios, is the ratio of the share of top 10 percent to the bottom 40 percent of households (Palma, 2006, 2011; Cobham & Sumner, 2013).

There more than hundred statistical or econometric tests for analysing disparities (Maio, 2007), but one needs to have good reasons or at least pragmatic reasons to decide which ones to use. The Gini-coefficient is the most cited measure of inequality, so it is a good idea to use this. Following SDG 10.1, it would seem to make sense also to calculate the Palma Ratio (i.e., the ratio of the richest 10% of the population's share divided by the poorest 40%'s share). This research study has used Gini-coefficient, and Palma Ratio for measurement of asset disparities in Punjab (Pakistan).

4. RESULTS AND DISCUSSION

4.1 Dimensional structure of items for the Asset Index

The results of Exploratory Factor Analysis with Promax oblique rotation provide evidence of six correlated factors with eigenvalues higher than 1. We have applied Cronbach's alpha

criterion to assess the reliability of these six factors. For a reliable asset index, only those assets are included in the scale that result in an increase in reliability, i.e., 22 assets out of the 30. The Cronbach's alpha results show that the asset index should be comprised of the items included in correlated factors F1, F2 and F3, while the indicators which are grouped into factors F4, F5 and F6 should be dropped due to their low value of Alpha (see Table 1). The reliability coefficient of the index was improved from 0.84 to 0.87 by dropping eight assets. (i.e., only including 22 items).

Table 1 Loadings of EFA and Tetrachoric-PCA

Exploratory Factor Analysis (EFA) loadings with Oblique Promax Rotations (Sorted)				Tetrachoric PCA Loadings with Oblique Rotations (Sorted)		
Factors	Asset	Factor Scores	Alpha	Sr. no.	Assets	Factor1
Factor 1	Refrigerator	0.77	0.85	1	Washing Machine	0.89
	Washing machine	0.76		2	Refrigerator	0.89
	Finished Flooring of Dwelling	0.70		3	Iron	0.86
	Knitting machine	0.64		4	Air conditioner	0.85
	Iron	0.59		5	Cooking range	0.85
	TV	0.58		6	Finished flooring	0.85
	Motorcycle	0.56		7	Computer	0.81
	Pump (Water)	0.55		8	Electricity	0.77
	Gas	0.48		9	Gas	0.74
	Bank Account	0.45		10	Television	0.73
	Mobile	0.45		11	Phone	0.72
	Finished walls dwelling	0.41		12	Car	0.70
	Watch	0.41		13	Bank	0.68
	Finished roofing of dwelling	0.41		14	Pump	0.68
Factor 2	Air conditioner	0.80	0.77	15	Knitting machine	0.68
	Cooking range	0.75		16	Finished walls	0.64
	Car	0.70		17	Water filter	0.63
	Phone (Landline)	0.67		18	Mobile	0.63

	Water filter	0.56		19	Electric Fan	0.58
	Computer	0.54		20	Motorcycle	0.52
Factor 3	Fan	0.88	0.82	21	Finished roofing	0.52
	Electricity	0.88		22	Watch	0.47
Factor 4	Land owned	0.74	0.59	23	Bus	0.18
	Animals	0.70		24	Radio	0.13
	Tractor	0.59		25	Tractor	0.11
	Animal-cart	0.55		26	Boat	0.04
Factor 5	Boat	0.78	0.25	27	Bicycle	-0.03
	Bus	0.76		28	Land	-0.08
Factor 6	Bicycle	0.77	0.05	29	Animal-cart	-0.22
	Radio	0.43		30	Animals	-0.47

Table 1 also shows results of tetrachoric PCA loadings with oblique rotation. These results confirm that 22 items have a correlation with factor 1 higher than 0.4 and the rest of the eight items are not strongly associated with this factor. This suggests that these assets (i.e., bus, radio, tractor, boat, bicycle, land, animal-drawn cart and animals) should not be included in an asset index construction at household level in Punjab. The results of EFA and Tetrachoric PCA are consistent.

4.2 Item Response Theory (IRT)

Cronbach's Alpha is a Classical Test Theory (CTT) based measure of reliability. This approach has several limitations, e.g., (a) it assumes a linear relationship between the latent variable and observed scores, (b) reliability cannot be estimated directly so assumptions need to be made which are unlikely to be met in practice (Rusch et al., 2017). In the 1960s, to overcome the limitations of CTT, IRT was introduced by Georg Rasch and Allan Birnbaum (Embretson & Reise, 2000). There are broadly three types of IRT models⁴: the one-parameter logistic model,

⁴ The formula is:

$$= ci + (1 - ci) \frac{e^{a_i(\theta - b_i)}}{1 + e^{a_i(\theta - b_i)}} \quad (\text{IRT Model})$$

two-parameter logistic model and polytomous models. (Embretson & Reise, 2000; Streiner & Norman, 2003). In this paper, we have used the two-parameter logistic (2PLM) model. This model measures both severity (first parameter) and discrimination (second parameter). The first parameter scores show, in units of standard deviation from the average household, the estimate of how asset rich or asset poor a household is likely to be that possesses a particular asset. The second IRT model parameter, the discrimination score, shows how well each asset discriminates between asset rich and asset poor households.

Figure 1 represents the ‘S’ shaped item characteristic curve of the two parameter IRT model. The ability of each asset to measure severity is shown by the position of each asymptotic curve along the X-axis. For example, if the position of the curve is further to the right, the absence of this asset would represent a lower living standard of the household. The ability of each item to discriminate between the asset poor and asset rich households is shown by how vertical each curve is with respect to the Y-axis. If the curve is more upright that means it has a better discriminating ability and higher correlation with the asset index. Preferably, a good asset index would be exemplified by a series of fairly vertical ‘S’ shaped curves spread out along the X-axis. The midpoint between the upper and lower asymptotes is known as the inflection point on curve. The inflection point for the assets (e.g., radio, tractor, boat, bicycle, landownership, animal cart, and animals) lie either below -3 or above +3 standard deviations from the average household are not included in this figure. More precisely, the discrimination is shown by steepness of the curve and a steeper curve means the item can discriminate between asset poor and asset rich households in a better way.

Figure 1 IRT Results for the 22 Assets Retained for Asset Index after the Validity and Reliability Tests

Table 2 shows the two-parameter IRT results for each of the 30 items. The severity parameter scores in column 2 measure the standard deviation units from the mean value. The lowest value of the severity score is for bicycle ownership and the highest values are for possession of a boat, tractor or bus. The severity criterion acceptability thresholds are set at ± 3 standard deviations from the mean value. All those items are dropped with the severity score equal to or greater than 3 or equal to or less than -3 standard deviations. So, for reliable measurement of the asset index, these all items are excluded from the analysis.

Table 2 IRT Results for the 30 Indicators of Asset Index

Sr. no.	IRT Results ⁵		
	Item Name	Difficulty	Discrimination
1	Bicycle	-14.53	-0.03
2	Land	-5.85	-0.08
3	Animal-drawn Cart	-5.03	-0.23
4	Mobile	-2.31	0.63
5	Fan	-1.94	0.75
6	Electricity	-1.80	0.95
7	Finished roofing of dwelling	-1.72	0.50
8	Finished walls of dwelling	-1.58	0.70
9	Iron	-1.09	0.87
10	Knitting machine	-0.63	0.68
11	TV	-0.63	0.72
12	Pump	-0.62	0.67
13	Finished flooring f dwelling	-0.42	0.83
14	Animal	-0.25	-0.45
15	Washing machine	-0.14	0.89
16	Refrigerator	-0.09	0.86
17	Motorcycle	0.10	0.47
18	Watch	0.20	0.41
19	Gas	0.49	0.71
20	Bank account	0.68	0.65
21	Computer	1.21	0.81
22	Cooking range	1.45	0.91
23	Air conditioner	1.55	0.93
24	Phone	1.91	0.81
25	Car	1.97	0.79
26	Water filter	2.63	0.76
27	Radio	10.08	0.17
28	Bus	10.30	0.30
29	Tractor	13.93	0.12
30	Boat	37.25	0.11

Notes: The highlighted cells, in column 3, are those with difficulty threshold scores below -3 or above +3 and, in column 5, are those with correlation threshold score below 0.4.

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⁵ IRT 2PL is applied, sorted by difficulty scores and run the transformation: $\left\{ a / \sqrt{(3.29 + a^2)} \right\}$ on the discrimination parameter for correlation range -1 to +1. Rule for exclusion of item for severity score is ≥ 3 or ≤ -3 & for correlation is ≤ 0.4 . Log likelihood is -402407.28.

Similarly, the discrimination criterion was also applied to drop unsuitable items for a reliable measurement of the asset index. The transformed correlation⁶ ranges between -1 and +1. All assets with correlations below 0.4 were dropped, this was the threshold value used by Guio et al. (2012). The same eight assets fail both the severity and discrimination test and were dropped from the analysis.

The reliability of the final 22 item asset index was formally assessed using Confirmatory Factor Analyses to calculate Omega, which was .87, indicating that the final asset index is a highly reliable measure for the Punjab (Pakistan).

To conclude, this paper has applied factor analysis, tetrachoric PCA to identify the dimensional structure of items for the asset index and used CTT and IRT for reliability analysis. The reliability analysis suggested that we can include 22 items for the final asset index construction as these 22 items form a highly reliable scale, inclusion of any of the other 8 asset items would increase the amount of random error of the index, i.e., it would be a worse measure of living standards.

Table 3 Household's Ownership of Assets (List of Assets) and different tests.

Sr. No.	Information about Items' Ownership		Exploratory Factor Analysis ⁷	Comparing TET _{PCA} , CTT and IRT		
	Does your household own this asset?	Possible Answer		Tetrachoric PCA	IRT Results suggests	Cronbach's Alpha ⁸ suggests
1	Refrigerator	Yes/no	Factor 1	Selected	Selected	Selected
2	Washing Machine/Dryer	Yes/no	Factor 1	Selected	Selected	Selected
3	Knitting/Sewing Machine	Yes/no	Factor 1	Selected	Selected	Selected
4	Iron	Yes/no	Factor 1	Selected	Selected	Selected
5	Television	Yes/no	Factor 1	Selected	Selected	Selected
6	Dunky Pump/Turbine	Yes/no	Factor 1	Selected	Selected	Selected

⁶ IRT 2PL is applied, sorted by severity and run the transformation: $\left\{ a / \sqrt{(3.29 + a^2)} \right\}$ on the discrimination parameter for correlation range -1 to +1. Rule for exclusion of item for correlation is ≤ 0.4 . Log likelihood is -402407.28.

⁷ The results of EFA suggested 6 factors, all items in the list are arranged & coloured according to factors.

⁸ The results of Cronbach's Alpha suggested these items/factors could be excluded on the basis of scale reliability coefficient value. After dropping these items over all Reliability coefficient has improved from .84 to .87.

7	Mobile Phone	Yes/no	Factor 1	Selected	Selected	Selected
8	Motorcycle	Yes/no	Factor 1	Selected	Selected	Selected
9	Watch	Yes/no	Factor 1	Selected	Selected	Selected
10	Bank Account	Yes/no	Factor 1	Selected	Selected	Selected
11	Gas	Yes/no	Factor 1	Selected	Selected	Selected
12	Finish flooring of dwelling	Yes/no	Factor 1	Selected	Selected	Selected
13	Finished walls of dwelling	Yes/no	Factor 1	Selected	Selected	Selected
14	Finished roofing of dwelling	Yes/no	Factor 1	Selected	Selected	Selected
15	Air Conditioner	Yes/no	Factor 2	Selected	Selected	Selected
16	Cooking Range/Micro Wave	Yes/no	Factor 2	Selected	Selected	Selected
17	Car	Yes/no	Factor 2	Selected	Selected	Selected
18	Telephone	Yes/no	Factor 2	Selected	Selected	Selected
19	Computer	Yes/no	Factor 2	Selected	Selected	Selected
20	Water Filter	Yes/no	Factor 2	Selected	Selected	Selected
21	Electricity	Yes/no	Factor 3	Selected	Selected	Selected
22	Fan/Water Cooler	Yes/no	Factor 3	Selected	Selected	Selected
23	Land	Yes/no	Factor 4	Dropped	Droppe	Dropped
24	Animals	Yes/no	Factor 4	Dropped	Droppe	Dropped
25	Tractor	Yes/no	Factor 4	Dropped	Droppe	Dropped
26	Animal-drawn Cart	Yes/no	Factor 4	Dropped	Droppe	Dropped
27	Boat	Yes/no	Factor 5	Dropped	Droppe	Dropped
28	Bus	Yes/no	Factor 5	Dropped	Droppe	Dropped
29	Bicycle	Yes/no	Factor 6	Dropped	Droppe	Dropped
30	Radio	Yes/no	Factor 6	Dropped	Droppe	Dropped

4.3 Validity of the Asset Index

The correlation of household income from all sources (adjusted for household size) with each asset was calculated to test the validity of each item. We used the Luxembourg Income Study and OECD square root equivalisation scale method to allow for household economies of scale (e.g., OECD, 2008, 2011). This equivalisation scale divides household income by the square root of household size. Figure 2 shows the ANOVA main effect plot of all 22 assets, on the vertical axis, the log of equivalised household disposable income, the X axis shows the possession or not of each asset (coded 1 for possession and zero for non-possession).

Figure 2 ANOVA main effect plot of 22 Assets by Equalized Household Income

In Figure 2, the right-hand dot on each graph presents the estimated average incomes of those who own the particular asset, and the left-hand dot depicts the estimated average incomes of those who do not own that asset. This figure shows that households which own each asset have a higher equivalised household income on average. Therefore, all of the 22 assets appear to be valid on this test.

Figure 3 below illustrates the positive relationship between household income and the asset ownership index which provides a worthwhile ex-post validation of the index. The figure shows the mean log of equalized disposable income and the 95% confidence interval of the mean associated with each asset index score. Figure 3 confirms the *a priori* assumption that low-income households would own fewer assets and high-income households would own a larger number of assets - this relationship is non-linear.

Figure 3 Mean equalized disposable income, by asset index score

4.4 The Asset Index: district level analysis

The difference between rural and urban living standards is significant, the average score for urban areas is .62 compared with .44 for rural areas of Punjab. District level analysis of the asset index is presented in Figure 4. This shows that Lahore has the highest average asset index score of .67; followed by Gujrat and Sialkot with .63 and .62, respectively. At the other end of the scale, the district of Rajanpur has the lowest asset index in Punjab at .34; followed by Muzaffar Gar and DG Khan (all districts are from the same administrative division) with scores of .37 and .39, respectively. This variation of asset index among the different districts reflects significant economic disparities among the divisions and districts of Punjab.

Figure 4 Average Asset Index Score: Punjab Districts

Figure 5 Within District difference between Urban-Rural Asset Index Scores

Figure 5 shows the significant differences between average asset scores in urban and rural areas of each district of the Punjab. There are particularly large urban/rural disparity in DG Khan, Rahimyar khan, Sahiwal and Multan.

4.5 Asset disparities within the Punjab

This section explains the asset disparities across the 36 districts of Punjab by using the Gini-coefficient and Palma ratio. The Palma Ratio as a measure of disparity is based on the reflection of José Gabriel Palma that in many countries about half of the national income goes to the middle class and that this income share is relatively stable. Therefore, inequality can meaningfully be measured by comparing the incomes of the bottom 40 percent (the poorest)

and top 10 percent (richest) of households (Cobham and Sumner, 2013). A comparison of Gini and Palma results are presented at the end of this section.

4.6 Results of Gini-Coefficient

An intuitive interpretation of the Gini-coefficient is presented by Raskall and Matheson (1992) as follows. If there are two households selected at random from the income distribution and the difference between their incomes is expressed as a proportion of mean income, then this difference is twice the value of the Gini-coefficient. For example, if the value of Gini-coefficient is .20, it means that expected difference between two randomly selected households would be 40% of the average income. Overall, the value of the coefficient for Punjab is .22, For rural Punjab, it is .24 and .15 for urban areas. This means that the expected difference between two randomly selected households in rural Punjab would be 48% of the average permanent income share as measured by the asset index.

The province of Punjab is divided into nine divisions, with the divisions Dera Ghazi Khan and Bahawalpur having the highest asset disparities. Gini-coefficient values are .32 and .26, respectively. The divisions Gujranwala, Rawalpindi and Lahore are more equal with asset Gini-coefficients of .16, .16 and .18, respectively. The results seem to reflect the reality of the situation in the Punjab. Gujranwala Division is known as a hub of industrial units like Sialkot, Gujrat and Gujranwala districts, with better living, employment and education opportunities. On other hand, DG Khan and Bahawalpur are part of south Punjab, characterized by lower access to education, employment and safe-drinking water access.

Out of the 36 districts of Punjab, the five districts with the highest inequality are Rajanpur, DG Khan, Muzaffar Gar, Layyah and Bhakkar with coefficient values of .33, .33, .31, .28 and

.27, respectively. The five districts with the lowest inequality include Sialkot, Lahore, Gujrat, Chakwal, and Gujranwala with Gini values of .14, .14, .14, .15 and .15, respectively.

4.7 Results of the Palma Ratio

Out of nine divisions, the highest asset inequality is in Dera Ghazi Khan (DG Khan), where the bottom 40%, on average, has only 18% of the assets and the richest 10% has 20% of the assets (highest among 9 divisions of Punjab). The Palma and Gini results are consistent in identifying DG Khan as the most unequal division. Similarly, Gujranwala and Rawalpindi are the most equal divisions with a Gini of 0.16 and Palma ratios of 0.52 and 0.52, respectively.

Table 4 District wise Bottom 40% & Top 10% Asset Shares and Inequality results

Sr. No	District	Bottom 40 %	Top 10%	Palma Ratio	Gini-coefficient
1	Rajanpur	15.1	21.3	1.41	0.34
2	DG Khan	16.8	20.7	1.23	0.33
3	M. Garh	18.9	20.7	1.1	0.31
4	Layyah	20.6	18.5	0.9	0.28
5	Bahwalpur	21.1	18.1	0.97	0.27
6	RY Khan	21.1	18.2	0.86	0.27
7	Bhakkar	21.2	18.4	0.86	0.27
8	B. Nagar	22.0	18.0	0.82	0.26
9	Jhang	21.6	17.4	0.81	0.26
10	Khushab	23.1	17.5	0.76	0.24
11	Lodhran	23.1	17.2	0.74	0.24
12	Multan	23.1	16.8	0.73	0.23
13	Khanewal	23.4	16.9	0.72	0.23
14	Chiniot	23.8	17.1	0.72	0.23
15	Mianwali	24.2	16.6	0.69	0.22
16	Sahiwal	24.4	16.7	0.68	0.22
17	Okara	24.3	16.6	0.68	0.22
18	Pakpattan	25.1	16.9	0.67	0.21
19	Vehari	25.3	16.3	0.64	0.21
20	Sargodha	25.9	16.2	0.63	0.20
21	Hafizabad	26.3	15.7	0.60	0.19
22	N. Sahib	26.5	15.8	0.59	0.19
23	Kasur	27.1	15.9	0.59	0.19
24	TT Singh	26.8	15.4	0.58	0.18
25	Faisalabad	28.1	15.3	0.55	0.17
26	Attock	27.9	15.0	0.54	0.17
27	M. Bahaudin	28.1	15.1	0.54	0.17
28	Sheikhupura	28.6	14.9	0.52	0.16

29	Jhelum	29.3	15.0	0.51	0.16
30	Narowal	28.5	14.6	0.51	0.16
31	Rawalpindi	29.0	14.8	0.51	0.16
32	Gujranwala	29.8	14.6	0.49	0.15
33	Chakwal	29.7	14.2	0.48	0.15
34	Gujrat	30.4	14.4	0.47	0.14
35	Sialkot	30.5	14.4	0.47	0.14
36	Lahore	30.5	14.2	0.46	0.14
	Punjab	24.2	16.6	0.69	0.22

Table 4 shows the Gini-coefficient and asset shares of the bottom 40%, and the top 10% for each district of Punjab. In Punjab, on average, the bottom 40% of the population (poorest) has 24% of the assets and the top 10% (richest) people have 17% of the assets. Figure 7 shows that the bottom 40% share ranges between 15% and 31% (district Rajanpur and Faisalabad, respectively) and the top 10% share ranges between 14% to 21% (district Lahore and Rajanpur, respectively).

Hence, the asset distribution in the district Rajanpur is the most unequal with the bottom 40% of the population receiving only 15% of asset share (lowest in Punjab) and the richest 10% receiving 21% (highest in Punjab), with a Palma ratio 1.41 and Gini-coefficient of 0.34. At the other end of the scale, the least asset disparities are in Lahore District, with the bottom 40% receiving around 31% (highest in Punjab) and the top 10% getting 14% (lowest in Punjab), with a Palma ratio of 0.46 and Gini-coefficient of 0.14 (second lowest in Punjab).

4.8 Palma versus Gini

In general, a strong correlation is expected between the Palma ratio and the Gini-coefficient index. Figure 6 shows an exponential association offering a nearly perfect fit for the Palma and Gini relationship. The Gini is sensitive towards the middle of the distribution, while Palma excludes the middle 50% from the analysis. Nevertheless, both methods produce effectively identical results about asset inequality in the districts of the Punjab. This demonstrates the

validity of the key assumption of the Palma Ratio method that the middle 50% of the distribution can be ignored due to the low variability in this part of distribution.

Figure 6 The Palma Ratio and Gini-coefficient Relationship

We have investigated which are the key components of the Palma ratio for explaining the high correlation with the Gini-coefficient using Ordinary Least Square (OLS) regression Table 5 shows the results of the regression analysis. Nearly all variation in Gini-coefficient is explained by the top 10% and bottom 40% of households. The positive sign for the top 10% shows that a rise in the share of the top 10% recipients will cause an increase in inequality (Gini) in Punjab. The negative sign for the bottom 40% indicates that rise in the share of the poorest 40% of people will cause a reduction in overall inequality (Gini). Thus, the variability in the top 10% and bottom 40% shares of household assets effectively explain all the variance in the Gini (Inequality).

Table 5 OLS results (Gini by top 10% and bottom 40%)

VARIABLES	(1) Model 1
Log (bottom 40%)	-0.151*** (0.0229)
Log (top 10%)	0.267*** (0.0357)
Constant	-0.0504 (0.173)
Observations	36
R-squared	0.994

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

The Palma measure assumes that the middle class is highly stable across the time and across countries and that the important variation is amongst the bottom 40% and top 10% (Cobham & Sumner, 2013). This study has demonstrated that this is also true in the Punjab. The Palma ratio is arguably the superior measure of inequality because of it is much easier to understand. For example, if the value of Gini-coefficient index is 0.5, that indicates a serious problem of inequality but, for a non-technical audience, it has little intuitive meaning. On other hand, if the Palma ratio is 5.0, this can easily be translated into a meaningful statement that the richest 10% have five times more than the poorest 40%.

5. CONCLUSION

The main objectives of this study were to construct a valid and reliable asset index at household level and to estimate economic disparities in the 36 districts of Punjab (Pakistan) by using MICS micro-data. An asset index is a better measure than current income or expenditure for gauging a household's long-term capacity for buying goods and services and its potential resilience to economic shocks. The leading challenge for construction of asset indices is the selection of an optimum sub-set of indicators to form a valid and reliable index. Filmer & Pritchett (2001) used Principal Component Analysis (PCA) for selecting and weighting

indicators to construct an asset index. This methodology and the weights that it produces are highly questionable, particularly when the underlying data about assets is binary in nature. This research has used binary responses of households regarding ownership of asset (i.e., do you own it? – ‘Yes’ or ‘No’) and statistically appropriate latent trait methods for asset index construction. The dimensional structure of the available asset data was determined using Exploratory Factor Analysis (EFA) and Tetrachoric Principal Component Analysis (PCA). The Classical Test Theory (CTT), and Item Response Theory (IRT) were used for the selection of a reliable household level asset index for Punjab. Moreover, this paper has applied Gini-coefficient and Palma Ratio for measurement of asset/economic disparities in Punjab (Pakistan).

There are significant differences between rural and urban living standards in the Punjab. Lahore has the highest average living standards, followed by Gujrat and Sialkot, by contrast Rajanpur, Muzaffargarh and DG Khan households had much lower average levels of asset possession. Out of 36 districts, the richest are either from Central Punjab or North-Punjab, while districts from South-Punjab have lower levels of average asset possession and high levels of asset inequality.

The districts situated along the GT (Grand Trunk) road (from Islamabad to Lahore) have better living standards with a low level of disparities. Thus, area-based resource allocation should have a greater focus on improving conditions for the poorest in D.G. Khan, Bhawalpur, Sargodha divisions. In particular, policy makers need to focus on Rajanpur, DG Khan, and R.Y. Khan Districts as a priority for uplifting household living standard. Moreover, this research also suggests the need for more focussed administrative efforts in uplifting the lives of people in the Saraiki Province districts.

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