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Harnessing Household Economic Vulnerability: Evidence from a Developing Economy

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Abstract: *The global impact of the coronavirus (COVID-19) outbreak has been enormous. COVID-19 has exacerbated human suffering, harmed the global economy, turned many people's lives upside down, and had a significant impact on the health, economic, environmental, and social sectors. The purpose of this study is to understand the impact of the COVID-19 pandemic on household food insecurity and well-being. Based on a national survey conducted by the Pakistan Bureau of Statistics in December 2020, we will be looking at the financial implications faced by households during COVID-19. Findings suggest that COVID-19 is positively associated with food insecurity and other dimensions which include income loss, health inaccessibility, reduced remittances, and, reduced social safety nets. Specifically, compared to a non-COVID-19 household, the food insecurity levels of a COVID-19 household increase significantly by 43.2 percentage points. Instrumenting for COVID-19 using various controls, we find that a standard deviation increase in COVID-19 is associated with a rise of 0.729 standard deviations in food insecurity. Our results are robust to alternative estimation approaches to addressing the endogeneity of COVID-19 and other sensitivity checks.*

Keywords: COVID-19, food insecurity, health inaccessibility, economic vulnerability, social well-being

JEL Classification: D6, I15, Q18

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1. Introduction

What techniques and procedures enable a developing economy to not only survive but also strive for recovery and resilience when faced with enormous problems that go beyond health crises and permeate every aspect of socioeconomic life? Who offers the crucial lifeline in difficult economic times? To properly comprehend the intricate web of interrelated vulnerabilities that develops during such crises, it's critical to first comprehend the different aspects of shocks, such as food insecurity, health system, income loss, reduced remittances, and the dwindling of social safety nets. Next, the paper address's role of informal social networks, a frequently ignored yet powerful force that silently thrives in the fabric of any developing society where formal social structures and institutional procedures frequently take center stage in addressing economic difficulties. Particularly in times of economic crisis, these networks, which are constructed via close ties, shared ideals, and mutual support, have the power to convert vulnerability into resilience.

Motivated by the research of (Bukari et al. 2022), which examines the COVID-19 pandemic's effects on poverty levels and household food insecurity in Ghana, our study seeks to extend this research to the Pakistani context. Pakistan is classified as a lower middle-income country by the World Bank for development, with a 2020 population of 227.19 million and a per capita income of $1,365. In the 2020 Human Development Report, Pakistan was rated 154 out of 189 economies. The country comprises four provinces—Punjab, Sindh, Khyber Pakhtunkhwa (KPK), and Baluchistan—alongside the territories, namely Islamabad Capital Territory, Gilgit-Baltistan, and Azad Jammu and Kashmir. The outbreak of the COVID-19 pandemic was officially acknowledged in Pakistan on February 26, 2020, marking the arrival of a daunting challenge. Pakistan has been classified among high-risk countries for food insecurity by the Global Food Security Index 2019. On average, 48% of Pakistan's population is food insecure, with rural areas having relatively high food insecurity (60.6% rural vs. 52.4% urban) ((UNICEF) 2011). COVID-19 quarantine policies have had extraordinarily negative consequences for Pakistan's food system, especially the supply chain, is which already precarious. In addition to the COVID-19 pandemic's direct health effects, legislative measures including travel and trade restrictions, social isolation, and the closure of formal and informal COVID-19 indicators have had a lessening impact on the economy (Swinnen and McDermott 2020). Further, Pakistan is home to a substantial population of informal workers who reside just above the poverty line. These individuals faced a significant reduction in their incomes due to the implementation of lockdown measures and the ensuing crisis. Without targeted social protection measures, there is a real risk of these workers slipping into poverty. Hence in 2020–2021, the government spend PKR230.907 billion on social protection to bolster various programs and assist the needy. This exceeds the government expenditure from the previous year by 21%. Hence, Pakistan's growth rates, which were already increasing slower than the regional average of 4.7% before the crisis, are being significantly impacted by the situation (Markhof 2020). Although the overall socioeconomic impact of the pandemic is documented well, the academic literature regarding the depth and breadth of the shock at the household level is still scarce. In this regard, our study provides pioneering research on the economic vulnerability across various socioeconomic dimensions of the household during the crisis period.

Using extensive national survey data of 6000 households from different rural and urban areas of Pakistan, we examine the complex relationships between household vulnerability and well-being in Pakistani households during the COVID-19 epidemic. We measure household vulnerability across these crucial aspects by constructing innovative indices that include food insecurity, income loss, health inaccessibility, reduced remittances, and, reduce social safety nets. As part of the research process, we use robust structural equation modeling tools to identify the relationships between various dimensions, resulting in a more comprehensive understanding of the complex interplay of socioeconomic factors. Additionally, we analyze the profound impact of the pandemic-induced shock on each of the five created dimensions using the two-stage least squares method. We identify informal loans from friends and family as a crucial instrumental variable to assess the impact of a shock. Finally, we investigate the variations in household vulnerability across education quartiles, income quartiles, and provinces in Pakistan during the pandemic period. By shedding light on the various socioeconomic effects of the pandemic, this research paper hopes to inform policy decisions and promote resilient societies.

Our findings can propose the following implications: The breadth of shock is significantly more than its depth. The impact of COVID-19 is visible across all socioeconomic dimensions, however, the shock is short-lived. The rollback from the psychological impact of this unprecedented economic uncertainty is an actual challenge for developing economies. The presence of simultaneity bias reveals the endogenous nature of the shock. The impact of the shock on the food insecurity domain is significantly higher compared to all other dimensions. Informal social acquaintances provide a crucial lifeline during periods of economic uncertainty. The pandemic-induced shocks had a less severe effect on economically stable households while having a more negative impact on the unemployed and the least educated. Similarly, on the macro level provinces with better governance had a less severe impact compared to other provinces of Pakistan.

The rest of the paper is organized as follows: The literature review, which has been evaluated and merged, was the subject of section 2. The study's methodological concerns are primarily discussed in section 3 after which section 4 analyses the study's findings and conclusions. The study's suggestions and policy implications are presented in Section 5, along with the study's conclusion.

2. Literature review

Although there is a lot of literature on COVID-19, it is heavily weighted in favor of keeping the epidemic under control, as well as the dark consequences at the macro level. However, a comprehensive understanding of the pandemic's true impact at the micro level remains unclear. The Food and Agriculture Organization (FAO) report claims that the COVID-19 pandemic poses the greatest risk to those already battling with poverty, poor health, and hunger (Shahzad et al. 2021). Quarantine, social isolation, travel bans, and transportation limitations as a result of COVID-19 policy actions have reduced household earnings and led to unemployment. Access to food depends upon the income level and availability of resources of the households (HE Evans 2016; Maxwell 1996). The ability of those who have been relegated to purchase food is impacted by a decrease in income. Those with low incomes, who already consume little food, further cut back, making the situation about food security worse (Leach et al. 2020).

In the context of Pakistan, the following studies shed light on various dimensions, including employment, poverty, healthcare, education, and government policies. An integrative data analysis approach by (Rasheed et al. 2021) reveals that agriculture, education, and health care are just a few of the primary, secondary, and tertiary economic sectors that have been negatively impacted by the pandemic. An online survey by (Ali et al. 2021) investigates how the rural, mountainous community of Gilgit-Baltistan perceives the COVID-19 pandemic's socioeconomic effects. The responses of 367 participants revealed that the region is facing several serious issues, including food insecurity, income loss, fear of losing a job, and financial uncertainty. (Shafi et al. 2020) conduct an online survey of 184 Pakistani micro, small, and medium-sized enterprises, and their findings indicate that the majority of the enterprises have been significantly impacted and are dealing with a variety of problems, including financial, supply chain disruptions, a decline in demand, decreased sales, and decreased profits, among others. Additionally, the majority of businesses failed both preparation and a strategy to deal with this kind of scenario. A systematic review by (Azam et al. 2020) investigates how COVID-19 affects Pakistan's economy, education system, and poverty line and suggests that the only way to stop this epidemic is for the government to have control over the population. Other solutions include an online education system with better cyber-management, strict social segregation at work, testing and tracing policies for employees, quick informational strategies about new patients, medication, and health promotion policies. A study by (Narjis et al. 2024) reveals that the institutionalization of emergency social assistance with considerably wider coverage is necessary to address the economic shock brought on by pandemics like COVID-19. Based on survey data from 1500 households in urban Pakistan collected both before and after the COVID-19 outbreak, (Shams and Kadow 2022) discover that subjective well-being decreased during the early stages of the pandemic, especially among the unemployed, married couples, men, and elderly people. Following-up data from July 2020, on the 1005 parents and children interviewed immediately before COVID-19, shows that the epidemic has had a disproportionately harmful impact on the most vulnerable households' financial and emotional health (Baranov et al. 2022).

Hence, the literature concludes that the exceptional COVID-19 pandemic and the social and economic responses that follow (such as job losses, stay-at-home orders, business closures, and school closures) have the potential to significantly worsen food insecurity and the health disparities that it is associated with among already vulnerable people (Loopstra 2020). However, to explore the various impacts of the COVID-19 pandemic, this research aims to use precisely selected and trustworthy country-specific data. To acquire objective insights and reduce any potential subjective biases, we attempt to properly examine the data using rigorous analytical procedures. This method enables us to respond to socioeconomic questions with greater accuracy and provide a thorough picture of the socioeconomic consequences of the pandemic.

3. Methodology

3.1. Data and Design

A dataset comprising 6000 households (500 blocks) was collected by the Pakistan Bureau of Statistics in December 2020 from different rural and urban areas of Pakistan. The Population & Housing Census 2017 frame is used for designing the sample for this survey. Two-stage stratified random sample design has been adopted. In the first stage, primary stage units from both rural and urban areas of different provinces using systematic random sampling with the Probability Proportional to Size (PPS) method. In the second stage, 12 households have been selected using a systematic random sampling technique with equal probability in urban and rural areas. The data provides information about the socioeconomic impact of Covid-19 in terms of employment/ job loss, impact on income, food security, coping strategies adopted, and assistance received for tackling the shock.

3.2. Preliminary Data Analysis

The household survey data is complex since the data is collected in various modules and each module contains a bunch of nominal, multiple response, and continuous indicators. The data is collected from all individuals residing in a household for the employment and income section whereas in the remaining sections, the data is collected on a household level. We perform data merging using left join and only the household head (or son/daughter) data is used for the income and employment section. Another issue is the large number of missing values for various indicators. However, missing value analysis is not carried out to keep the data characteristics intact. But to reduce the number of indicators, the construction of composite variables in each dimension is carried out before the main analysis. The transformation not only reduced the number of indicators significantly but also improved the data scale.

3.3. Measurement of Variables

3.3.1. Dependent Variables

The dependent variables are food insecurity, income loss, health inaccessibility, reduced remittances, and reduced social safety nets.

3.3.2. Independent Variable

The study's independent variable was a measured shock of COVID-19. The variable is self-reported and measured on 5- a point Likert scale indicating the severity level of the household ranging from "not at all affected" to "severely affected".

3.3.3. Covariates

We control for household characteristics. The selection of the control variables comes from the Multidimensional Poverty Index (MPI) (Alkire et al. 2014). The objective of MPI is to quantify and track deprivation using ten distinct indicators and three key dimensions. Indicators include child mortality, nutrition, years of education, enrollment, access to water, sanitation, power, cooking fuel, floor quality, and asset ownership. These indicators encompass health, education, and living conditions dimensions. We consider education and living standard domain and thus the study includes the following indicators: electricity access, drinking water access, improved sanitation, cooking fuel, wall material, asset ownership, overcrowding, years of schooling, child school attendance, and the presence of dependents in the household. Few indicators were measured in a survey, while others are constructed as per the guidelines of MPI.

3.4. Empirical Model Specification and Estimation Strategy

Since we transform the indicators in each dimension on an interval scale, we construct indices across the following dimensions i.e., food insecurity, income loss, health inaccessibility, reduced remittances, and reduced social safety nets through Principal Component Analysis (PCA). It is assumed that some of the observed variables are connected for the PCA idea to work (O'Rourke et al. 2005). Finally, the extracted component scores for each dimension are combined to create a unique index through bootstrapping formative construction method. Next, we used the decision trees to validate the index scores, using chi-square statistics to find the best splits. CHAID, or Chi-squared Automatic Interaction Detection, is a classification technique for creating decision trees. A decision tree is a type of supervised machine learning algorithm where the predictions for the training and test dataset are based on the optimal splits of the input features. Our input features include the indices scores across all dimensions to predict three cases: First is the COVID-19 impact on households (high versus low), next is the job loss (yes and no) and the third one is changed in donations across three categories (increase, decrease, and no change). The training test split of 70:30 is considered and method accuracy is judged by performance on the confusion matrix. Hence, the procedure provides a reasonable validation tool for exploratory and confirmatory analysis.

Once five dimensions of household vulnerability are validated, next we estimate the empirical model as specified in the following equation

$$Y = \mathrm{X}\gamma + \beta\mathrm{Covid19} + \epsilon \tag{1}$$

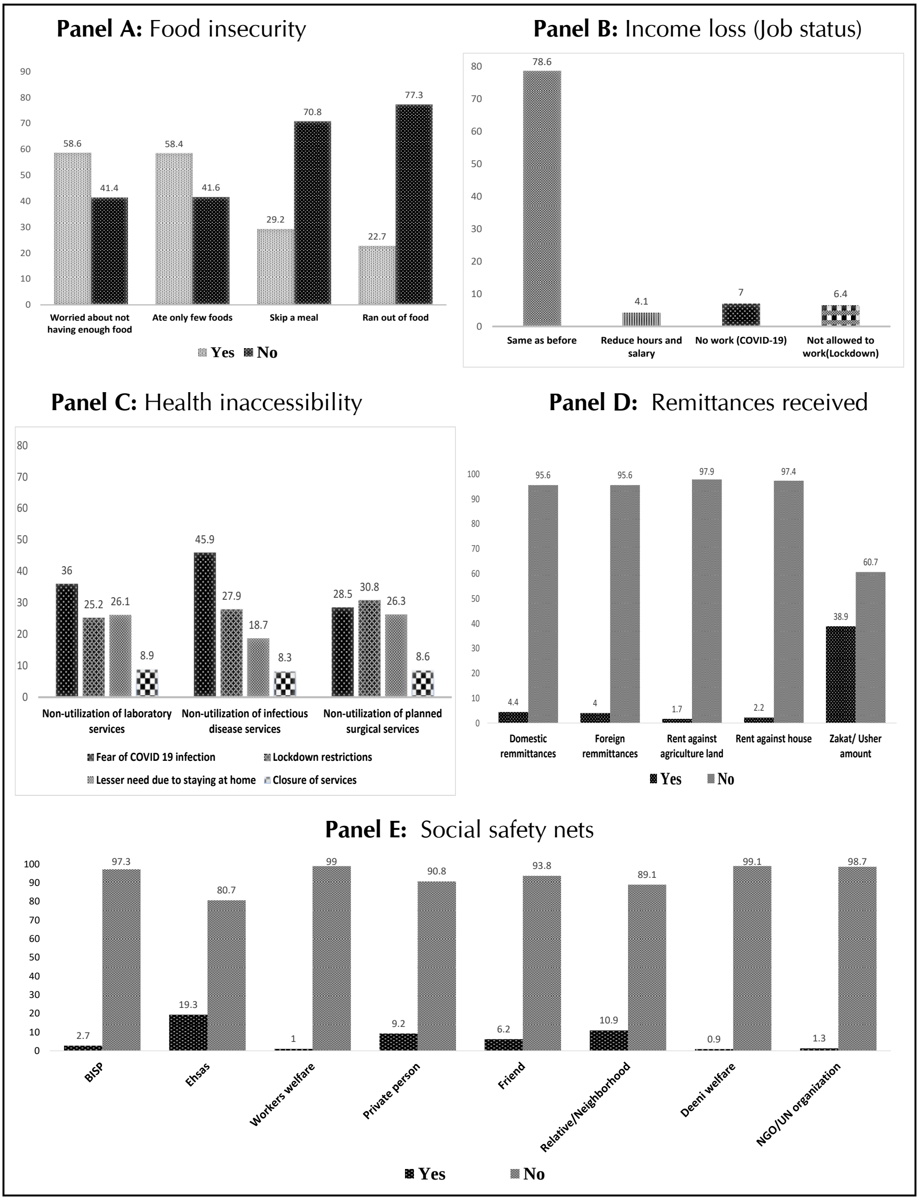
where Y is a vector of dependent variables, X is a matrix of nine control variables, γ is a vector of coefficients, Covid19 is the measured shock, and vector β is the impact of the shock on each of the five dimensions. Ordinary Least Square (OLS) is used to estimate equation (1) at first, which causes endogeneity problems in the link between the COVID-19 influence and our estimated household dimensions. The omitted variable bias, which typically happens when the error term is linked with an independent variable, is one potential source of endogeneity in equation (1). This can further cause underestimation or overestimation of the COVID-19 coefficient. Moreover, it is challenging to rule out more than one missing variable in a multivariate regression framework, similar to how our study was, making it hard to forecast the direction of bias (Forbes 2000). Another form of endogeneity that might skew our estimations in eq. (1) is measurement error in measuring COVID-19 severity of the household. To eradicate the issues of endogeneity, we executed instrumental variable estimation. Extensive research across twenty to thirty indicators reveals that informal loans from various sources like friends and family are a key predictor in defining the household shock severity and hence a good instrument for COVID-19. The literature validates the evidence of the relationship between the effect of loans and their outcome during times of crisis like COVID-19 (Berger et al. 2022) and (Bertogg and Koos 2022). Another key instrument is the social distancing for COVID-19 in measuring the health inaccessibility dimension. Various research studies show that social distancing helped significantly in reducing COVID-19 cases in different countries across the globe. According to (Pedersen and Favero 2020) social distancing is an effective method of containing the spread of COVID-19, but only if everyone will participate, and suggests that public servants should work to inform and convert the populace to the benefits of social distancing. We implemented the instrumental variable approach using the standard two-stage least squares (2SLS) method. To validate the selection of our instruments, we apply the generated instrumental variable approach and Lewbel 2SLS (2012) approach too. The Lewbel 2SLS approach combines internally produced instruments based on a heteroskedastic covariance restriction and external instruments. The adequacy of the suggested model is tested against various tests: The first one is the Kleibergen-Paap LM statistic where the null hypothesis assumes that the model is under-identified. The second one is the Wald F statistic which tests whether the suggested instruments are weak. Next, the Hansen J test assumes the null hypothesis that the instruments are valid. Finally, the DW–Hausman statistic which whether the variable under consideration can be treated as exogenous. Lastly, the robustness checks are conducted employing the simultaneous quantile regression technique, to examine the behavior of the model at different quantile levels instead of mean regression only. The presence of consistent behavior across various quantiles serves as compelling evidence of the model's robustness and reliability.

4. Empirical results and discussion

4.1. Descriptive Statistics

Figure 1 presents the descriptive statistics of key raw indicators across studied dimensions. The descriptives reveal that the psychological impact of the shock on food insecurity (Fig1: Panel A) is significant across Pakistani households. This is evident by the majority of responses towards worrying about less food, skipping a meal, or being unable to have a healthy meal. However, we still believe that the impact is moderate as the majority of the households respond that they never ran out of food because of a lack of money or other resources. Further, the descriptives (Fig1: Panel B) reveal that the income status in the majority of the sample households remains similar and the pandemic does not impact the income status significantly. Similarly, the psychological impact of health services inaccessibility (Fig 1: Panel C) observe more prominent compared to the actual impact. This is evident by the majority of the responses towards fear of COVID-19 infection, lockdown restrictions, or lesser need instead of services closures in various health checkup domains. The data structure complexity increased as our raw indicators reveals a very small proportion of sample households received domestic and foreign remittances and hence examining determinants of this domain and projection beyond the sample becomes a complicated problem. However, one interesting fact reveals in this domain (Fig 1: Panel D) is that in developing countries like Pakistan during periods of economic uncertainty, Zakat or Sadqat (a form of Islamic donation) always works better compare to other sources of receiving amounts. Fig 1: Panel E presents descriptive statistics for the social safety nets indicating the proportion of cash/ benefit received from different sources like family, friends, zakat, BISP or welfare trust, etc. during COVID-19. Although the numbers indicate inadequate coverage of social safety nets in Pakistan, however, the descriptives reveal that during the shock period, the Ehsas program for COVID-19, friends support, neighborhood or relative support provides better coverage compared to International NGOs.

Figure 1: Descriptive statistics of key indicators



4.2. Data Preparation

The household survey data is complex since the data is collected in various modules and each module contains a bunch of nominal, multiple response, and continuous indicators. The data is collected from all individuals residing in a household for the employment and income section whereas in the remaining sections, the data is collected on a household level. We perform data merging using left join and only the household head (or son/daughter) data is used for the income and employment section. Another issue is the large number of missing values for various indicators. However, missing value analysis is not carried out to keep the data characteristics intact. But to reduce the number of indicators, the construction of composite variables in each dimension is carried out before the main analysis. The description is provided in Appendix Table 6a. The transformation not only reduced the number of indicators significantly but also improved the data scale.

4.3. Principle Component Analysis (PCA) results

Once the composite indicators are formed, next we use principal component analysis to calculate factor scores. The objective is to construct sub-dimension indices (component scores) where item redundancy should not be an issue.

Table 1 presents the results of the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests conducted on the dimensions under study. The KMO measure assesses the adequacy of the sample for the analysis. Although the KMO value is below the suggested threshold (>0.6) for dimensions such as income loss, reduced remittances, and reduced social safety nets, we justify the suitability of our method because the composite scores in each dimension are derived from raw indicators across various scales, resulting in a low observed correlation. However, Bartlett's test of sphericity indicates that the correlations between items are sufficiently large for principal component analysis (PCA) across all dimensions. A preliminary analysis was conducted and components with eigenvalues greater than 1 were retained for further analysis. In the case of food insecurity, a single component was extracted, which accounted for 74.289% of the variance. Consequently, we named this component "food insecurity". For the income loss dimension, the first two components (both with eigenvalues greater than 1) were extracted, explaining a total of 68.297% of the data variation. We labeled the first latent sub-dimension as "reduce income" and the second latent sub-dimension as "reduce working hours". Likewise, in the domain of health inaccessibility, two components were extracted, accounting for 67.290% of the data variation. These components were named "issues faced in health services" and "issues faced in disease treatment". Regarding the reduced remittances dimension, the two extracted components explained 71.143% of the data variation. They were labeled as "amount received from remittances or rent" and "amount received from Zakat". Finally, applying PCA to the social safety nets dimension yielded two component scores that accounted for 61.763% of the data variation. These components were named "Government or NGO support" and "Private support".

Table 1: Principal component analysis results

	Eigenvalue	Proportion	Cumulative
Food insecurity			
Component 1	**2.229**	**74.289**	**74.289**
Component 2	.585	19.495	93.784
Component 3	.186	6.216	100.000
KMO overall	0.624		
Bartlett's Test of Sphericity	7243.536***		
Income Loss			
Component 1	**1.047**	**34.903**	**34.903**
Component 2	**1.002**	**33.385**	**68.287**
Component 3	.951	31.713	100.000
KMO overall	0.499		
Bartlett's Test of Sphericity	11.766***		
Health inaccessibility			
Component 1	**2.851**	**47.513**	**47.513**
Component 2	**1.187**	**19.777**	**67.290**
Component 3	.739	12.323	79.614
Component 4	.667	11.121	90.735
Component 5	.480	8.003	98.738
Component 6	.076	1.262	100.000
KMO overall	0.688		
Bartlett's Test of Sphericity	15417.079***		
Reduced remittances			
Component 1	**1.134**	**37.808**	**37.808**
Component 2	**1.000**	**33.335**	**71.143**
Component 3	.866	28.857	100.000
KMO overall	0.500		
Bartlett's Test of Sphericity	100.198***		
Reduced social safety nets			
Component 1	**1.408**	**35.206**	**35.206**
Component 2	**1.062**	**26.557**	**61.763**
Component 3	.937	23.428	85.192
Component 4	.592	14.808	100.000
KMO overall	0.500		
Bartlett's Test of Sphericity	1023.584***		

Note: $**p < 0.01$, $*p < 0.05$

4.4. Formative construction of various dimensions

Once the factor scores are calculated for each dimension, next we proceed to the formative construction of five dimensions namely Food Insecurity, Income loss, Health inaccessibility, Reduced remittances, and reduced Social Safety Nets using Bootstrapping framework. The model is formative because we believe each latent sub-dimension indicates different aspects of the same concept. We perform an estimation with the partial least square (PLS) method. To assess the level of collinearity, we look into the values the of Variance Inflation Factor (VIF). As shown in Table 2, all the VIF values are less than '5'. This justifies the validity of formative construction. Next, the significance of outer weights is assessed. Table 3 shows the results of outer weights for our constructs. The significance of outer weights indicates the importance of included indicators in the formation of constructs. Since component 1 extracts the highest amount of data variance in each dimension, hence we justify the imbalance of one highly significant and one insignificant indicator.

Table 2: Variance inflation factor for Outer Model

	Income loss		**Food insecurity**	**Health inaccessibility**		**Reduced remittances**	
	Reduce income	Reduce working hours	Food insecurity	Issues faced in disease treatment	Issues faced in services	The amount received from rent or remittances	The amount received from Zakat
VIF	1.00	1.008	1.085	1.000	1.003	1.000	1.017
	Reduced social safety nets						
	Govt. or NGO support	Private support					
VIF	1.027	1.000					

Table 3: Outer weights

	Original Sample (O)	Sample Mean (M)	Standard Deviation	T Statistics	P Values
Reduced income-→ Income	0.082	0.202	0.241	0.339	0.735
Reduced working hours→Income	-0.997	-0.903	0.263	3.796	0.000
Food insecurity→ Food insecurity	1.000	1.000	0.000	2.836	0.005
Issues Faced in disease treatment→ Health	0.374	0.426	0.227	1.648	0.100
Issues faced in services-→ Health	0.928	0.841	0.242	3.829	0.000
The amount received from rent or remittances-→ Remittances	-0.992	-0.611	0.472	2.102	0.036
The amount received from Zakat-→ Remittances	0.127	0.429	0.468	0.270	0.787
Govt. or NGO support--→ Social safety nets	0.216	0.535	0.349	0.618	0.537
Private support-→ Social safety nets	0.976	0.699	0.317	3.081	0.002

4.5. Construct validation using decision trees

Once the composite indicators are formed for each dimension, next the validity analysis is carried out using decision trees in a machine-learning framework. The goal is to analyze the predictive power of defined dimensions in answering the following three questions: First, the Covid-19 impact on households, second job loss during the pandemic period, and last is the change in amount/cash received before and after COVID-19. The original dataset is divided in the ratio of 70-30 for which 70 percent is added to the training sample and 30 percent to the test sample. Table 5 shows in the case of the COVID-19 impact on households, the model predicts 83% of instances correctly both in training and test sample. Similarly, in predicting the job loss our defined dimensions work well with an accuracy of around 98% both in training and test samples. Finally, the model performance remains consistent with 94% of cases identify correctly in case of predicting the change in donations received before and after COVID-19. Hence, the process validates our defined constructs across all dimensions.

Table 4: Decision tree results

Panel A: COVID-19 impact on Household (in two categories) Classification

Sample	Observed	Predicted		
		Less affected	More affected	Percent Correct
Training	Less affected	3082	182	94.4%
	More affected	539	311	36.6%
	Overall Percentage	88.0%	12.0%	82.5%
Test	Less affected	753	36	95.4%
	More affected	137	85	38.3%
	Overall Percentage	88.0%	12.0%	82.9%

Panel B: Job loss (Domestic or Foreign) Classification

Sample	Observed	Predicted		
		Yes	No	Percent Correct
Training	Yes	63	54	53.8%
	No	0	4272	100.0%
	Overall Percentage	1.4%	98.6%	98.8%
Test	Yes	16	18	47.1%
	No	0	1088	100.0%
	Overall Percentage	1.4%	98.6%	98.4%

Panel C: Change in donations received Classification

Sample	Observed	Predicted			
		Increase	Decrease	No Change	Percent Correct
Training	Increase	1684	0	0	100.0%
	Decrease	56	0	0	0.0%
	No Change	37	0	0	0.0%
	Overall Percentage	100.0%	0.0%	0.0%	94.8%
Test	Increase	379	0	0	100.0%
	Decrease	11	0	0	0.0%
	No Change	8	0	0	0.0%
	Overall Percentage	100.0%	0.0%	0.0%	95.2%

4.6. Baseline Regression Results

The baseline data regarding the impact of COVID-19 on five studied dimensions which include food insecurity, income loss, health inaccessibility, reduced remittances, and reduced social safety nets are shown in Table 5. Here, the COVID-19 variable is measured on 5- a point

Likert scale indicating the severity level of households ranging from "not at all affected" to "severely affected". Therefore, a "COVID-19 household" refers to a moderately to seriously impacted household for ease of interpretation, while a 'non-COVID-19 household' refers not-at-all to the mildly affected household. As shown in Table 5, we find that the impact of shock across all five dimensions is highly significant, however, the impact on food insecurity is more compared to other dimensions. In particular, a COVID-19 household's levels of food insecurity rise dramatically by 42.3 percentage points when compared to a non-COVID-19 household. In other circumstances, similar findings have been observed (Gundersen et al. 2021; Mishra and Rampal 2020; Pereira and Oliveira 2020). The issue with OLS results is the high proportion of unexplained to explained variation. It is intuitive since the inherent nature of defined household dimensions of economic vulnerability is complex and hence the shock even in controlled regression explains a very small amount of variation. Except for the food insecurity dimension, the R-square of COVID-19 shock on all other four dimensions is less than 10%. This emphasizes the significance of taking into consideration unobserved variables and their possible influence on the outcome, as failure to do so may result in biased or incomplete results.

Table 5: Standard regression estimates on the effects of COVID-19 on dimensions

	Food Insecurity	Income loss	Health Inaccessi-bility	Reduced Remittances	Reduced Social Safety Nets
COVID-19	0.4239**	0.1132**	0.1238**	0.0770**	0.1534**
	(0.0103)	(0.0123)	(0.0123)	(0.0127)	(0.0120)
Electricity access	0.0077	0.0329	-0.2915**	-0.0082	-0.2512**
	(0.0562)	(0.0671)	(0.0669)	(0.0692)	(0.0655)
Drinking water	0.3088**	0.0300	0.1875**	-0.0025	-0.0074
access	(0.0594)	(0.0710)	(0.0708)	(0.0732)	(0.0693)
Improved	-0.1111	-0.1403*	0.2364**	-0.0190	-0.1062
Sanitation	(0.0585)	(0.0699)	(0.0696)	(0.0720)	(0.0682)
Cooking fuel	-0.1357*	-0.1153	-0.2230**	-0.1005	-0.0441
	(0.0583)	(0.0697)	(0.0695)	(0.0719)	(0.0680)
Wall material	-0.2100**	0.0773	-0.6569**	0.0308	-0.1824**
	(0.0625)	(0.0747)	(0.0744)	(0.0770)	(0.0729)
Assets ownership	-0.3432**	-0.0197	-0.0556	-0.0843*	-0.0667
	(0.0346)	(0.0413)	(0.0412)	(0.0426)	(0.0403)
Overcrowding	-0.0143*	-0.0003	-0.0114	0.0034	0.0021
	(0.0067)	(0.0080)	(0.0080)	(0.0083)	(0.0078)
Years of schooling	-0.2438**	-0.0540	0.0364	-0.0973*	-0.0007

	Food Insecurity	Income loss	Health Inaccessi-bility	Reduced Remittances	Reduced Social Safety Nets
	(0.0396)	(0.0473)	(0.0472)	(0.0488)	(0.0462)
Child school attendance	-0.119 (0.0282)	0.0119 (0.3378)	-0.0123 (0.3367)	0.0361 (0.0348)	-0.0949** (0.0329)
N	5243	5243	5243	5243	5243
Adjusted R-squared	0.3125	0.0183	0.0442	0.0109	0.0470

Note: Robust standard errors adjusted for heteroscedasticity in parentheses $^{**}p < 0.01$, $^{*}p < 0.05$

4.7. Sensitivity to endogeneity

We run an instrumental variable approach to answer omitted variable bias and measurement error issues. In Table 6, we analyze three different methods: (1) the Two-stage least square method with external instruments (2) generated instrumental variable approach where the instruments are created from a provided set of covariates (3) the Lewbel 2SLS (2012) approach which combines external instruments with internally generated instruments. In terms of model adequacy, we conclude that 2SLS performs better compared to the other two methods. This is justified by the following statistical tests: The null hypothesis of the Kleibergen-Paap LM test assumes that the suggested model is under-identified. Our analysis indicates the rejection of the null hypothesis at a 1 % level of significance in all cases. Next, the Cragg-Donald Wald F-statistic measures that the suggested instruments of the model are weak. In the case of the 2SLS method, our analysis rejects this hypothesis at a 1% level of significance across all dimensions. In the case of generated IV method, the null hypothesis of the Wald F-test is accepted in all dimensions. This validates our selection of instrumental variables and the covariates too. Further, for the 2SLS method, the null hypothesis of the Hansen J statistic is accepted at a 1% level of significance in all dimensions which explains that the instruments are valid. In this case, the Lewbel 2SLS method does not perform well. This indicates that the external instruments are adequate to overcome endogeneity and the internal instruments need not be included. Finally, the rejection of the null hypothesis of the Hausmann test for the 2SLS method across all dimensions' reveals that COVID-19 is an endogenous variable. We observe that there exists a significant upward bias in 2SLS coefficient estimates compared to the baseline regression result estimates. In this regard, we consider the "delta" introduced by (Ciacci 2021) which represents the coefficient of proportionality between a selection of observables and unobservables. Across five dimensions the coefficient of proportionality remains small. This validates the instrumental variable estimates.

Based on the outcomes of the initial stage, we find that loans from friends are a key instrument in defining the severity level of a shock for any household. This is further explained by Table 3a, where the path analysis reveals that loan from friends is a significant predictor of shock severity explaining 12 percent of its variation. Interestingly, the behavior is similar across all dimensions. Hence, we conclude that it could serve as a good instrument as its impact on shock severity is significantly higher compared to the outcome variables. Similarly, we identify a loan from an employer as a good instrument for explaining shock severity. Thus in periods of economic vulnerability, informal social acquaintances provide crucial lifelines in developing economies like Pakistan. Finally, in determining the impact of a pandemic on health inaccessibility we identify social distancing as a key instrument. Our estimation results are in line with what has been observed in other contexts (Cahiers et al. 2020; Gundersen et al. 2021; Pereira and Oliveira 2020).

Table 6: COVID-19, food insecurity, income loss, health inaccessibility, reduced remittances, and reduced social safety nets (IV results)

Variables	Food insecurity			Income loss			Health inaccessibility			Reduced remittances			Social Safety nets		
	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS
COVID 19	0.744**	0.646**	0.729**	0.344**	0.576**	0.366**	0.547**	0.645**	0.746**	0.111**	0.098	0.109**	0.348**	0.283	0.339**
	(0.050)	(0.152)	(0.048)	(0.057)	(0.169)	(0.056)	(0.054)	(0.041)	(0.154)	(0.025)	(0.051)	(0.024)	(0.058)	(0.162)	(0.056)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage															
Loans from friends	0.596**			0.570**						0.570**			0.564**		
	(0.028)			(0.028)						(0.028)			(0.028)		
Loans from formal sources				-0.180*						-0.180*					
				(0.069)						(0.069)					
Loans from employer				0.290**						0.290**			0.244**		
				(0.046)						(0.046)			(0.043)		
Region (Rural)							-0.361**								
							(0.037)								
Social distancing (Always)							-0.342**								
							(0.034)								
Coefficient of proportionality	0.755			0.131			0.758			0.010			0.519		
N	3741	3741	3741	3741	3741	3741	3741	3741	3741	3741	3741	3741	3741	3741	3741
Kleibergen-Paap LM test	380.42**	23.965*	389.482**	398.786**	23.965*	408.890**	348.608**	25.609*	368.264**	398.786**	23.965*	408.890**	398.786**	23.965*	408.890**
Cragg-Donald Wald F test	442.6**	4.584	37.462**	161.984**	4.585	35.442**	241.562*	3.645	34.614*	161.984**	4.584	35.442**	161.984**	4.548	35.442**
Hansen J test	0.000	18.330	17.350	2.351	23.748	35.589**	3.451	17.642	24.658*	1.725	19.745*	21.282	0.911	19.953*	21.054

Table 6: COVID-19, food insecurity, income loss, health inaccessibility, reduced remittances, and reduced social safety nets (IV results)

Variables	Food insecurity			Income loss			Health inaccessibility			Reduced remittances			Social Safety nets		
	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS	2SLS	Generated IV	Lewbel 2SLS
DW–Hausman test	36.519**	2.451	17.272**	6.973**	4.210	7.462**	45.321**	34.321**	7.649**	14.351**	3.037	11.177**	15.061**	1.298	15.671**
J P-value		0.074	0.137		0.013	0.001		0.213	0.312		0.049	0.094		0.046	0.1

Note: Columns 2, 5, and 8 represent 2SLS (Standard IV) estimates with instruments identified in Table 6. Columns 4, 7, and 10 represent Lewbel 2SLS results that combine internal and external instruments. The null hypothesis of the Kleibergen-Paap LM statistic assumes that the model is under-identified. The Wald F statistic measures weak instruments, with critical values varying between 5.53 and 16.38. The Hansen J statistic assumes the null hypothesis that the instruments are valid. The null hypothesis of the Hausman tests is that the variable under consideration can be treated as exogenous.

Robust standard errors adjusted for heteroscedasticity in parentheses

Standard coefficients in brackets $^{**}p < 0.01$, $^{*}p < 0.05$

4.8. Heterogeneity analysis

In this section, we conduct the heterogeneity analysis across provinces, income, and education quartiles. The result of COVID-19's effects across six distinct Pakistani provinces is shown in Table 7. The analysis reveals that Sindh is the most affected province in the food insecurity dimension. Although the impact on food insecurity is significant across all provinces, however, the magnitude of observed shock in Sindh is two times more compared to Gilgit Baltistan(GB). It is highlighted in the State Bank of Pakistan's third quarterly report (2018-19)[1] that food insecurity in Sindh and Balochistan is higher compared to (GB) and Khyber Pakhtunkhwa (KP) provinces. Further, the pandemic impact on food insecurity in Sindh is highlighted in IPC (May 2021) report[2] too. This validates our findings. The same behavior is observed in the income dimension where Sindh and Balochistan are most affected while KP and Punjab are the least. In health inaccessibility, the pandemic reveals a significant impact on Azad Jammu and Kashmir (AJK) and Sindh province. The study by (Nazeer et al. 2020) concludes that the spread of the pandemic in AJK is due to non-social distancing and non-compliance behavior. This justifies our selection of social distancing instruments for household pandemic severity in the health inaccessibility domain. The impact of the shock on remittances is highest in AJK province. The evidence makes sense because AJK is home to 1.5 million people who are working abroad and remittances play a significant role in their livelihoods[3]. The shock impact on the social safety net appears significant in all provinces except GB and AJK provinces. The justification is the low coverage of schemes like "Ehsas emergency funds" in these two regions (Markhof 2020).

Table 7: COVID-19 and provinces across each dimension

Variables	**COVID - 19**				
Provinces	**Food Insecurity**	**Income Loss**	**Health Inaccessibility**	**Reduced Remittances**	**Reduced Social Safety Nets**
	0.4079**	0.0969**	-0.0266	0.1329**	0.1500**
KP	(0.0253)	(0.339)	(0.0205)	(0.0261)	(0.0295)
Punjab	0.3942**	0.0841**	0.0178	0.0869*	0.1529**

[1] https://www.sbp.org.pk/reports/quarterly/fy19/Third/qtr-index-eng.htm
[2] IPC_Pakistan_Sindh_Acute_Food_Insecurity_2021MarSept_Report.pdf
[3] https://www.sbp.org.pk/sbp_bsc/FieldOff/Mfb/mfb-intro.pdf

	(0.0194)	(0.0192)	(0.0140)	(0.0329)	(0.0215)
Sindh	0.5095**	0.2232**	0.1568**	0.0048	0.1324**
	(0.0197)	(0.0241)	(0.0297)	(0.0083)	(0.0224)
Baluchistan	0.4850**	0.1435**	0.0186	0.0290**	0.1451**
	(0.0244)	(0.0382)	(0.0170)	(0.0104)	(0.0374)
Gilgit	0.2211**	-0.0531	0.1060	0.1130	0.0847
Baltistan	(0.0458)	(0.1269)	(0.0724)	(0.0994)	(0.0715)
AJ &	0.3010**	0.0975*	0.5694**	0.4796**	0.1960
Kashmir	(0.0269)	(0.0499)	(0.0825)	(0.0714)	(0.0618)
Controls	Yes	Yes	Yes	Yes	Yes
N	5243	5243	5243	5243	5243

Note: Robust standard errors adjusted for heteroscedasticity in parentheses $^{**}p < 0.01$, $^{*}p < 0.05$

In Table 8, income is divided into four quartiles, from less-income household brackets to high-income households. Due to variations in the socioeconomic factors of the homes, there appears to be a variance in COVID-19's effects at the household level. The results are almost significant for each bracket but low-income households are more affected and become vulnerable as compared to the high-income households. These findings concur with those of related studies (Leach et al. 2020; Wolfson and Leung 2020).

Table 8: COVID-19 and income quartile across each dimension

Variables	**COVID - 19**				
Income Quartile	**Food Insecurity**	**Income Loss**	**Health Inaccessibility**	**Reduced Remittances**	**Reduced Social Safety Nets**
Less than Rs. 12,000	0.5025**	0.4457*	0.1649**	0.0426**	0.0997**
	(0.0195)	(0.0209)	(0.0271)	(0.0099)	(0.0243)
Between Rs. 12,000 & Rs. 18,500	0.4101**	0.1185**	0.1126**	0.0700**	0.1663**
	(0.0220)	(0.0262)	(0.0256)	(0.0133)	(0.0265)
Between Rs. 18,500 & Rs. 30,000	0.3451**	0.1016**	0.1008**	0.0732**	0.1224**
	(0.0210)	(0.0246)	(0.0234)	(0.0183)	(0.0228)
Above Rs. 30,000	0.3272**	0.1364**	0.1105**	0.1104**	0.1275**
	(0.0225)	(0.0311)	(0.0245)	(0.0529)	(0.0264)
Controls	Yes	Yes	Yes	Yes	Yes
N	5243	5243	5243	5243	5243

Note: Robust standard errors adjusted for heteroscedasticity in parentheses $^{**}p < 0.01$, $^{*}p < 0.05$

Table 9 reflects the impact of COVID-19 on each dimension across four education quartiles. The results are quite interesting for the health inaccessibility dimension. Households having more educated individuals tend to have better health as compared to less educated household individuals. More years of education are typically linked to greater health (Fujiwara and Kawachi 2009). Education affects employment prospects and income, which may in turn affect health. Education may also increase awareness of healthy lifestyle choices, leading to better time and product usage decisions that benefit health (Kenkel 1991). These findings concur with those of related studies (Arendt 2005; Li and Powdthavee 2015).

Table 9: COVID-19 and education quartile across each dimension

Variables	**COVID - 19**				
Education Quartile	**Food Insecurity**	**Income Loss**	**Health Inaccessibility**	**Reduced Remittances**	**Reduced Social Safety Nets**
Less than 4 years	0.4498** (0.0197)	0.0973** (0.0219)	0.1299** (0.0230)	0.0440** (0.0135)	0.1403** (0.0248)
Between 4 & 6 years	0.4493** (0.0180)	0.1185** (0.0218)	0.0722** (0.0200)	0.0845** (0.0279)	0.1302** (0.0201)
Between 6 & 7 years	0.4126** (0.0272)	0.1049** (0.0348)	0.0483 (0.0305)	0.0772** (0.0235)	0.1929** (0.0298)
Above 7 years	0.4357** (0.0237)	0.1022** (0.0286)	0.0776* (0.0252)	0.0792** (0.0339)	0.1621** (0.0249)
Controls	Yes	Yes	Yes	Yes	Yes
N	5243	5243	5243	5243	5243

Note: Robust standard errors adjusted for heteroscedasticity in parentheses $^{**}p < 0.01$, $^{*}p < 0.05$

4.9. Robustness Checks

To analyze the impact of COVID-19 on the complete conditional distribution rather than the mean of studied socioeconomic dimensions, we use the simultaneous quantile regression (SQR) method. For this, we have divided each dimension into four quantiles. From Table 10, we can see that the results are quite consistent for each quantile across each particular dimension. This concludes that our model is robust and our analysis is appropriate because there is no change across the quantiles.

Table 10: Simultaneous Quantile Regression (SQR)

Variables	COVID – 19					
	Simultaneous Quantile Regression (SQR)					
	Lowest	Second	Third	Highest	Controls?	N
Food Insecurity	0.5892** (0.0444)	0.8135** (0.0578)	0.8671** (0.0737)	0.6558** (0.0876)	Yes	3787
Income Loss	0.0549* (0.0247)	0.2665** (0.0242)	0.2593** (0.0322)	0.1384** (0.0187)	Yes	3787
Health Inaccessibility	0.0261** (0.0088)	0.1738** (0.0325)	0.3867** (0.0825)	1.4930 (0.1434)	Yes	5259
Reduced Remittances	0.0014** (0.0002)	0.0043** (0.0003)	0.0118** (0.0006)	0.0205** (0.0012)	Yes	3787
Reduced Social Safety Nets	0.0699** (0.0142)	0.1784** (0.0200)	0.8520** (0.0204)	0.4420** (0.0829)	Yes	3741

Note: Robust standard errors adjusted for heteroscedasticity in parentheses $**p< 0.01$, $*p< 0.05$

5. Conclusion and Policy Implications

The main objective of this research was to investigate the influence of COVID-19 on various aspects of households in Pakistan such as food insecurity, health accessibility, income loss, reduced social safety nets, and reduced remittances. The study utilized data collected at the national level from households in Pakistan and found that COVID-19 has indignant the well-being of households. Specifically, the pandemic worsened the issue of food insecurity in Pakistan. It made many people more food insecure and forced several people who weren't impoverished before the outbreak into poverty. The results of the current study also showed that socioeconomic factors have a big impact on how much the pandemic affects household livelihoods. For instance, pandemic-induced shocks had a less severe effect on economically stable households while having a more negative impact on the unemployed and the least educated. We conclude that COVID-19 has increased the breadth of vulnerability to hunger, income loss, remittances, social safety nets, etc which is likely to make existing policy measures inefficient or outright useless. The study's conclusions have various policy implications. To better equip homes to survive the challenges posed by a pandemic of this kind, income production activities that give dependable sources of income to households are of the highest importance. Additionally, the government should prioritize finding jobs for households since, as this study demonstrated, income loss is higher for those who are jobless or lost their jobs as a result of the epidemic than for others. Giving businesses financial aid and other retention incentives is a tenable strategy for protecting household jobs. Additionally, to improve low-income households' access to food and other necessities, social protection programs like direct cash transfers to vulnerable groups in society are needed to be expanded.

The study includes significant limitations that should be taken into account, however, their combined impact cannot diminish the significance of the study's conclusions. Due to the cross-sectional nature of the data, no past data was used to analyze trends of similar economic shocks on food insecurity and other factors. More information about the nature of the relationship between COVID-19 and socioeconomic domains might have come from trend analysis. Again, the main indicator of COVID-19's impact was the self-reported "household shock severity level" which inherently includes measurement bias. Further, this lacked sufficient detail. Future studies to assess the effect of COVID-19 on households are advised to incorporate additional metrics.

References

(UNICEF), U. N. C. F. (2011). Pakistan National Nutrition Survey 2011. *Pakistan National Nutrition Survey*, 1–84. http://www.mhinnovation.net/sites/default/files/downloads/innovation/research/Pakistan National Nutrition Survey 2011.pdf

Ali, A., Ahmed, M., & Hassan, N. (2021). Socioeconomic impact of COVID-19 pandemic: Evidence from rural mountain community in Pakistan. *Journal of Public Affairs*, *21*(4). https://doi.org/10.1002/pa.2355

Alkire, S., Conconi, A., Seth, S., Gonzalez de Alba, I., John, A., Kanagaratnam, U., et al. (2014). for their support and substantive input. We also wish to thank special advisorAlkire, S., Conconi, A., Seth, S., Gonzalez de Alba, I., John, A., Kanagaratnam, U., Lu, S., Mancilla Garcia, M., Oldiges, C., Roa-Clavijo, F., Van Tran, Q., Apablaza, M., Ballo, (June), Deutsch, J., Silber, J. (2005). Measuring multid. https://www.ophi.org.uk/wp-content/uploads/Global-MPI-2014-Brief-Methodological-Note-and-Results.pdf

Arendt, J. N. (2005). Does education cause better health? A panel data analysis using school reforms for identification. *Economics of Education Review*, *24*(2), 149–160. https://doi.org/10.1016/j.econedurev.2004.04.008

Azam, T., Mohsin, M., Naseem, S., Nilofar, M., Zia-UR-Rehman, M., Nelofer, S., et al. (2020). Economic Growth Vulnerability Amid the COVID-19 Epidemic: A Systematic Review of Different Sectors of Pakistan. *Revista Argentina de Clínica Psicológica*, *29*(4), 705. https://doi.org/10.24205/03276716.2020.875

Baranov, V., Grosjean, P., Khan, F. J., & Walker, S. (2022). The impact of COVID-related economic shocks on household mental health in Pakistan. *Health Economics (United Kingdom)*, *31*(10), 2208–2228. https://doi.org/10.1002/hec.4571

Berger, A. N., Bouwman, C. H. S., Norden, L., Roman, R. A., Udell, G. F., & Wang, T. (2022). Is a friend in need a friend indeed? how relationship borrowers fare during the covid-19 crisis. *How Relationship Borrowers Fare during the COVID-19 Crisis (July 1,* *2022). Kelley School of Business Research Paper*, (2021–01).

Bertogg, A., & Koos, S. (2022). Who Received Informal Social Support During the First COVID-19 Lockdown in Germany, and Who Did Not? The Role of Social Networks, Life Course and Pandemic-Specific Risks. *Social Indicators Research*, *163*(2), 585–607. https://doi.org/10.1007/s11205-022-02890-0

Bukari, C., Aning-Agyei, M. A., Kyeremeh, C., Essilfie, G., Amuquandoh, K. F., Owusu, A. A., et al. (2022). Effect of COVID-19 on household food insecurity and poverty: Evidence from Ghana. *Social indicators research*, *159*(3), 991–1015.

Cahiers, L., Mouloudj, K., Bouarar, A. C., & Fechit, H. (2020). the Impact of Covid-19 Pandemic on Food يرثتأ ءباو ديفوك 19 ىلع نملأا يئاذغلا سويرف ناوروك ةعرسب افلمخ رئاسخ ةحداف في لك تاعاطقلا نودب ءانثتسا ، صخلم . عمو كلذ فلتخا مجح ررضلا نم عاطق رخلأ نمو دلب رخلأ . لاإ نأ ام مهي بوعشلا رشتنا ن يقبا تاجايتحلاا ىرخلأا, *36*, 159–184.

Ciacci, R. (2021). A Matter of Size : Comparing IV and OLS estimates, 1–17.

Forbes, K. J. (2000). A reassessment of the relationship between inequality and growth. *American economic review*, *90*(4), 869–887.

Fujiwara, T., & Kawachi, I. (2009). Is education causally related to better health? A twin fixed-effect study in the USA. *International journal of epidemiology*, *38*(5), 1310–1322.

Gundersen, C., Hake, M., Dewey, A., & Engelhard, E. (2021). Food Insecurity during COVID-19. *Applied Economic Perspectives and Policy*, *43*(1), 153–161. https://doi.org/10.1002/aepp.13100

HE Evans, P. N. (2016). Rural-urban relations, household income diversification and agricultural productivity, 1–23.

Kenkel, D. S. (1991). Health behavior, health knowledge, and schooling. *Journal of Political Economy*, *99*(2), 287–305.

Leach, M., Nisbett, N., Cabral, L., Harris, J., Hossain, N., & Thompson,

J. (2020). Food politics and development. *World Development*, *134*, 105024.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics*, *30*(1), 67–80.

Li, J., & Powdthavee, N. (2015). Does more education lead to better health habits? Evidence from the school reforms in Australia. *Social Science and Medicine*, *127*, 83–91. https://doi.org/10.1016/j.socscimed.2014.07.021

Loopstra, R. (2020). Vulnerability to food insecurity since the COVID-19 lockdown Preliminary report. *Food Foundation*, (April), 1–26. https://ukdataservice.ac.uk/.

Markhof, Y. (2020). Pakistan's social protection response to the COVID-19 pandemic: the adequacy of Ehsaas emergency cash and the road ahead, (188).

Maxwell, S. (1996). Food security: A post-modern perspective. *Food Policy*, *21*(2), 155–170. https://doi.org/10.1016/0306-9192(95)00074-7

Mishra, K., & Rampal, J. (2020). The COVID-19 pandemic and food insecurity: A viewpoint on India. *World Development*, *135*, 105068. https://doi.org/10.1016/j.worlddev.2020.105068

Narjis, S., Yaseen, M. R., Anwar, S., Sohail, M., & Makhdoom, A. (2024). THE SOCIO-ECONOMIC IMPACT OF COVID-19 ON HOUSEHOLDS IN PUNJAB, PAKISTAN, *4*(3).

Nazeer, Q., Sardar, T., & Mashhadi, S. F. (2020). E V A L U A T I O N O F C O V I D - 1 9 P A N D E M I C I N A Z A D J A M M U A N D K A S H M I R, *70*(6), 1913–1918.

O'Rourke, N., Hatcher, L., & Stepanski, E. J. (2005). *A step-by-step approach to using SAS for univariate & multivariate statistics*. SAS institute.

Pedersen, M. J., & Favero, N. (2020). Social Distancing during the

COVID-19 Pandemic: Who Are the Present and Future Noncompliers? *Public Administration Review*, *80*(5), 805–814. https://doi.org/10.1111/puar.13240

Pereira, M., & Oliveira, A. M. (2020). Poverty and food insecurity may increase as the threat of COVID-19 spreads. *Public Health Nutrition*, *23*(17), 3236–3240. https://doi.org/10.1017/S1368980020003493

Rasheed, R., Rizwan, A., Javed, H., Sharif, F., & Zaidi, A. (2021). Socio-economic and environmental impacts of COVID-19 pandemic in Pakistan—an integrated analysis. *Environmental Science and Pollution Research*, *28*(16), 19926–19943. https://doi.org/10.1007/s11356-020-12070-7

Shafi, M., Liu, J., & Ren, W. (2020). Impact of COVID-19 pandemic on micro, small, and medium-sized Enterprises operating in Pakistan. *Research in Globalization*, *2*. https://doi.org/10.1016/j.resglo.2020.100018

Shahzad, M. A., Qing, P., Rizwan, M., Razzaq, A., & Faisal, M. (2021). COVID-19 pandemic, determinants of food insecurity, and household mitigation measures: a case study of Punjab, Pakistan. In *Healthcare* (Vol. 9, p. 621). MDPI.

Shams, K., & Kadow, A. (2022). COVID-19 and Subjective Well-Being in Urban Pakistan in the Beginning of the Pandemic: A Socio-Economic Analysis. *Applied Research in Quality of Life*, 93–113. https://doi.org/10.1007/s11482-022-10114-3

Swinnen, J., & McDermott, J. (2020). COVID-19: Assessing impacts and policy responses for food and nutrition security. *IFPRI book chapters*, 8–12.

Wolfson, J. A., & Leung, C. W. (2020). Food insecurity and COVID-19: Disparities in early effects for us adults. *Nutrients*, *12*(6), 1–13. https://doi.org/10.3390/nu12061648

Appendix

Table 1a: Indicators transformation

	Original indicator	Method	Transformed indicator
Income loss	Status about working conditions (10 ordinal categories)	Merging	Reduced to four ordinal categories
Food insecurity	Four indicators representing food worry (nominal Yes/No category)	Weighted average using frequency method	Composite normalized indicator of food worry intensity (0-1 scale).
	Three indicators representing less available food (nominal Yes/No category)	Weighted average using frequency method	Composite normalized indicator of less food availability (0-1 scale).
	Three indicators represent ran out of food (nominal Yes/No category)	Weighted average using frequency method	Composite normalized indicator of food hunger intensity (0-1 scale).
Health inaccessibility	Major reasons for utilization of health services(9 multiple response nominal categories)	Creation of item response set and weighted average using frequency method	Composite normalized indicator representing health service utilization issues intensity for each household (0-1 scale).
	Major reasons for non-utilization of health services(9 multiple response nominal categories)	Creation of item response set and weighted average using frequency method	Composite normalized indicator representing health service non-utilization issues intensity for each household (0-1 scale).
Reduced remittances	Monthly average rent received from agriculture and non-agricultural resources(2 ratio scale indicators)	Merging	Composite indicator representing total rent received from all sources.
	The monthly average amount received from domestic and foreign remittances(2 ratio scale indicators)	Merging	Composite indicator representing total remittances received from all sources.

	Original indicator	Method	Transformed indicator
	The monthly average amount received from usher, sadaqat, and second occupation (2 ratio scale indicators)	Merging	Composite ratio scale indicator representing total amount received from all sources
Reduced social safety nets	The monthly average amount received from the Benazir income support program, Zakat, or social security(3 ratio scale indicators)	Merging	Composite ratio scale indicator representing total amount received from govt. support.
	The monthly average amount received from Deeni's welfare Trust, other Trusts, Family, Friends, and Relative (3 ratio scale indicators)	Merging	Composite ratio scale indicator representing total amount received from friends and family.

Table 2a: Definition of control variables

Control variables	Definition
Electricity access	Deprived if the household has no electricity
Drinking water access	Deprived if the household has no access to an improved source of water according to MDG standards: (tap water, hand pump, protected well, mineral water).
Improved sanitation	Deprived if the household has no access to adequate sanitation according to MDG standards: flush system (sewerage, septic tank, and drain).
Cooking fuel	Deprived if the household uses solid cooking fuels for cooking (wood, dung cakes, crop residue, coal, etc)
Wall material	Deprived if the household has unimproved walls (mud, mud bricks, wood/bamboo, etc)
Asset ownership	Deprived if the household does not have more than two small assets (radio, TV, fan, iron, sewing machine, air cooler, watch, etc) OR no large asset (refrigerator, computer, motorcycle) AND has no car.
Overcrowding	Deprived if the household is overcrowded (4 or more people).
Year of schooling	Deprived if no member in the household of school age has completed primary education.
Child school attendance	Deprived if son, daughter, or grand-child age less than 15 has not attended formal education.

Table 3a: Path analysis for instrumental variables identification

	Food Insecurity	Income loss	Health inaccessibility	Reduced remittances	Reduced Social Safety Nets
COVID-19	0.4263** (0.01635)	0.15055** (0.0201)	0.1366** (0.01192)	0.07914** (0.0684)	0.1094** (0.0203)
Loans from friends (Yes)	0.1023** (0.0302)	0.05876* (0.0376)		0.0363* (0.0173)	0.0386* (0.03802)
Loans from formal sources/ NGOs/Banks (Yes)		-0.01982 (0.08639)		0.0035 (0.0398)	-0.00410 (0.0874)
Loans from employer (Yes)		-0.00587 (0.0864)		0.0210 (0.0266)	0.03703* (0.0584)
Region (Rural)			0.0179 (0.0309)		
Social distancing (Always while outside)			-0.03502* (0.02947)		
R-squared	0.2220	0.0316	0.0219	0.0111	0.0197
COVID-19					
Loans from friends (Yes)	0.3414** (0.0277)	0.3189** (0.0283)		0.3189** (0.0283)	0.3189** (0.0283)
Loans from formal sources/ NGOs/Banks (Yes)		-0.0558** (0.0684)		-0.0558** (0.0684)	-0.0558** (0.0684)
Loans from employer (Yes)		0.1401** (0.0453)		0.1401** (0.0453)	0.1401** (0.0453)
Region (Rural)			-0.09640** (0.03489)		
Social distancing (Always while outside)			-0.1937** (0.0327)		
R-squared	0.1166	0.1327	0.0327	0.1327	0.1327

Note: Robust standard errors adjusted for heteroscedasticity in parentheses $^{**}p < 0.01$, $^{*}p < 0.05$

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