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Climate Vulnerability and Debt: How Energy and Road Access Shape Household Coping in Pakistan

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Does public infrastructure influence how people respond to climate shocks through borrowing? This study, using nationally representative household data merged with tehsil-level climate shocks, finds that rainfall shocks significantly increase the probability of household borrowing and the borrowed amount. It also shows that access to energy infrastructure significantly reduces the likelihood of household borrowing and the amount of debt. Access to road infrastructure reduces debt in normal conditions but increases it during climatic shocks. This study constructs a unique instrument, community-level access to media services, to address endogeneity in infrastructure. The heterogeneity analysis finds that poor and female-headed households face disproportionately higher debt burdens but derive greater financial protection from access to infrastructure. From a policy perspective, this study concludes that the availability of public infrastructure should be considered as a major factor in climate adaptation strategies.

Keywords: Household Debt, Climatic Shocks, Energy Infrastructure, Road Connectivity, Pakistan.

1. INTRODUCTION

Climate shocks threaten the financial stability of developing economies. The impacts of climate change, such as more frequent extreme events of droughts, earthquakes and heavy rainfall, have devastating effects on livelihoods, especially in low-income countries such as Pakistan (Mukherjee & Fransen, 2024). These climate shocks exacerbate financial distress by reducing income while increasing consumption needs (Kandikuppa & Gray, 2022; Dercon, 2004). However, access to public infrastructure, such as energy and roads, can mitigate these effects by stabilising income, improving connectivity, and reducing dependence on borrowing (Sovacool, 2012; Donaldson, 2018; Nawaz, 2021).

The literature on climate vulnerability and household debt indicates that climatic shocks exacerbate borrowing needs. Kandikuppa & Gray (2022) show that increased rainfall variability significantly raises household debt levels in rural India, while Acosta et al. (2021) highlight how climate shocks deepen poverty traps in developing economies. Similarly, Nawaz (2021) shows that energy poverty, when combined with climate-induced disruptions, increases health deprivation. However, limited attention has been paid to how public infrastructure moderates these vulnerabilities, especially in developing

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countries where infrastructure deficits remain pronounced (Bazilian & Pielke, 2013; Chakravarty & Tavoni, 2013). This research gap is particularly crucial for Pakistan, where around 30 percent households depend on borrowing from various sources such, as formal and informal (Javed, et al. 2019). This necessitates investigating how access to public infrastructure, mainly energy and road connectivity, can reshape household decision-making during climate shocks.

Given this background, this study examines the interplay among public infrastructure, climate shocks, and borrowing behaviour of households in Pakistan. Pakistan is economically fragile and highly vulnerable to climate change (Adnan, et al. 2024). Pakistan faces recurrent climate shocks that have increased poverty, food insecurity, and economic vulnerabilities (World Bank, 2024; GoP, 2023). The study empirically measures the impact of climate shocks, namely rainfall anomalies, on the likelihood of household borrowing and the amount borrowed. This study also examines how public infrastructure, such as energy and road connectivity, softens these effects using interaction terms. This design is consistent with theoretical frameworks indicating that infrastructure stabilises income and reduces financial dependence on loans during climatic events (Khandker, et al. 2009; Dinkelman, 2011; Churchill, et al. 2023). The study examines heterogeneity in borrowing responses across socioeconomic groups to establish the robustness of the analysis (Dercon, 2004).

This study uses the Household Integrated Economic Survey (HIES) 2018-19 to achieve the desired objectives. The HIES provides comprehensive information on borrowing patterns among households along with other socio-demographic characteristics. Pakistan Mouza Census 2020 is used to capture community infrastructure, public services, and environmental conditions, and rainfall shocks are constructed using CHIRPS satellite data. The MOUZA Census and CHIRPS satellite data are merged with HIES using tehsil-level identifiers. For robustness checks, this study uses alternative climate-shock proxies, such as droughts and earthquakes (Dercon, 2004; Acosta et al., 2021; Aggarwal, 2021; Hirvonen, 2016).

The empirical analysis yielded numerous key results. This study shows that the likelihood of borrowing decreased by 46 percent to 53 percent with an increase in household income, while larger households are 4.7 percent to 5.0 percent more likely to borrow and accumulate higher debt. Experience and literacy reduce the probability of borrowing by 18 percent to 30 percent, while the effects of gender vary across regions and sociocultural contexts. Energy access (odds ratios of 0.794–0.876) and metal-paved roads (odds ratios of 0.750–0.870) reduce the likelihood of borrowing and debt amount among households. On the other hand, rainfall shocks increase both the likelihood of borrowing (odds ratios 1.039–1.656) and debt amounts (coefficients 0.931–0.938) among households. The empirical analysis shows that access to energy significantly reduces financial pressures from rainfall shocks. In contrast, the interaction of rainfall shocks with road infrastructure increases the likelihood of borrowing.

The heterogeneity analysis shows that rainfall shocks increase the likelihood of borrowing across all income groups, with the poor more vulnerable (odds ratio 1.770) than the non-poor (odds ratio 1.622). More importantly, access to public infrastructure reduces the likelihood of borrowing, particularly for poor households, highlighting the important role of public infrastructure in financial stability for vulnerable groups. The gender-disaggregated analysis shows that rainfall shocks place greater borrowing pressure on female-headed households (odds ratio 1.794 versus 1.635). Additionally, energy access enhances financial stability for female-headed households by lowering debt

(–0.358). Road infrastructure effects are mixed: it significantly reduces debt for male-headed households (-0.209) but has no notable impact on female-headed households.

This study builds on previous research demonstrating financial vulnerabilities induced by climatic shocks by incorporating the moderating effects of infrastructure (Kandikuppa & Gray, 2022; Dercon, 2004). It provides a comprehensive framework linking climatic shocks, public services, and borrowing behaviour in a developing-country context, contributing to debates on building resilience and economic adaptation (Donaldson, 2018; Sovacool, 2012). It complements studies on the role of infrastructure in economic development by quantifying its interaction with climate-induced borrowing needs (Nawaz, 2021; Jacoby & Minten, 2009).

This study offers three key contributions to the literature. First, it reconceptualises household debt as a structural consequence of climate vulnerability rather than merely a neutral means of smoothing consumption, thereby guiding climate–household analysis towards an understanding of financial fragility and reliance on debt. Second, it presents causal evidence on the impact of public infrastructure by addressing the endogeneity of energy access with a new community-level instrument, media service access, which remains underexplored in climate debt research. Third, this study shows that, using different proxies, infrastructure not only reduces the likelihood of borrowing but also improves the sustainability of debt management during climatic shocks. This analysis offers a mechanism-based understanding of how infrastructure influences coping strategies in climate-vulnerable household contexts.

The rest of the paper is organised as follows: Section 2 presents the theoretical model. Section 3 provides a detailed discussion on methodology and data construction. Section 4 presents the results and discussion based on empirical analysis. The final section provides the conclusion.

2. THEORETICAL MODEL

This section presents a simple decision-making model to analyse the impact of climatic shocks on the borrowing decisions of households. It also provides a mechanism to study the moderating role of public infrastructure in the face of climate shocks, thereby ensuring financial stability. This model assumes that households face an optimisation problem where they aim to maximise utility (U_i) by deciding whether to borrow (L_i), a choice influenced by income (Y_i), consumption needs (C_i), access to public services (S_i), and exposure to environmental shocks (Z_i). This model is based on the basic principles of utility maximization among households (Deaton & Muellbauer, 1980; Deaton, 1992; Alem, et al. 2023). This model assumes that the borrowing decision is binary: $L_i = 1$ if the utility with borrowing (U^L) exceeds the utility without borrowing (U^N); otherwise, $L_i = 0$.

In the absence of shocks, borrowing decisions are determined by income, consumption needs, and public services. The utility functions are given as:

$$U_i^L = Y_i + BC_i - \gamma L_i + \delta S_i,$$

$$U_i^N = Y_i + BC_i + \delta S_i$$

where β represents the marginal utility of consumption, γ denotes the cost of borrowing, and δ captures the utility derived from public services. Households choose to borrow if:

$$U_i^L > U_i^N \rightarrow -\gamma L_i + \delta S_i > 0.$$

Public services (S_i) reduce borrowing dependency by alleviating financial constraints. For example, energy stabilises income (Sovacool, 2012; Nawaz, 2021; Bazilian and Pielke, 2013; Churchill, et al. 2022), and road infrastructure improves market connectivity (Donaldson, 2018; Jacoby & Minten, 2009; Nawaz & Mangla, 2021). Both reduce dependence on loans (Khandker, et al. 2009; Dinkelman, 2011; Churchill, et al. 2023). This implies:

$$\frac{\partial L_i}{\partial S_i} < 0$$

Climatic shocks, such as rainfall anomalies, droughts, or earthquakes, affect income and increase consumption needs, making borrowing more likely (Dercon, 2004; Acosta, et al. 2021; Aggarwal, 2021; Hirvonen, 2016). For example, agricultural households facing rainfall variability may experience reduced crop yields, leading to income shortfalls and higher borrowing needs (Waqas, et al. 2025; Premand & Stoeffler, 2022; Amare, et al. 2021; Trinh, 2018). In this case, the utility functions become:

$$U_i^L = Y_i + BC_i - \gamma L_i + \delta S_i - \theta Z_i$$

$$U_i^N = Y_i + BC_i + \delta S_i - \theta Z_i$$

where θ represents the utility loss caused by shocks. Borrowing occurs if:

$$U_i^L > U_i^N \rightarrow -\gamma L_i + \delta S_i - \theta Z_i > 0.$$

Climatic shocks reduce income and increase consumption needs:

$$Y_i' = Y_i - \theta Z_i, C_i' = C_i + \phi Z_i,$$

where $\phi > 0$ reflects the extent to which shocks increase consumption. Substituting these adjustments into the utility functions:

$$U_i^L = (Y_i - \theta Z_i) + \beta(C_i + \phi Z_i) - \gamma L_i + \delta S_i - \theta Z_i$$

$$U_i^N = (Y_i - \theta Z_i) + \beta(C_i + \phi Z_i) + \delta S_i - \theta Z_i.$$

The borrowing condition then becomes:

$$-\gamma L_i + \beta\phi Z_i + \delta S_i > 0$$

Households maximise utility by selecting the optimal loan amount (L_i^*) to offset shocks. The utility maximisation problem is:

$$\max L_i \quad U_i^L = (Y_i - \theta Z_i) + \beta(C_i + \phi Z_i) - \gamma L_i + \delta S_i - \theta Z_i$$

The first-order condition (FOC) for utility maximisation is:

$$\frac{\partial U_i^L}{\partial L_i} = -\gamma + \delta \frac{\partial S_i}{\partial L_i} = 0.$$

Assuming $\delta \frac{\partial S_i}{\partial L_i} = 0$ (Short-term public service availability), the optimal loan amount is:

$$L_i^* = \frac{\beta\phi Z_i}{\gamma}$$

Public services (S_i) interact with shocks (Z_i) to influence borrowing. Improved access to energy and roads mitigates the adverse financial effects of shocks by reducing borrowing needs. This interaction modifies the utility function:

$$U_i^L = Y_i + \beta C_i - \gamma L_i + \delta S_i - \theta Z_i + \phi(S_i \times Z_i).$$

The interaction term $(S_i \times Z_i)$ reduces the borrowing induced by shocks:

$$\frac{\partial^2 L_i}{\partial S_i \partial Z_i} < 0.$$

From this framework, the following hypotheses arise: (1) Climatic shocks (Z_i) increase the likelihood of borrowing ($\frac{\partial L_i}{\partial Z_i} > 0$) (Dercon, 2004; Aggarwal, 2021); (2) Public services (S_i) reduce borrowing ($\frac{\partial L_i}{\partial Z_i} < 0$) (Khandker, et al. 2009; Dinkelman, 2011; Churchill, et al. 2023); (3) The interaction between public services and shocks ($S_i \times Z_i$) mitigates the adverse effects of shocks on borrowing $\left(\frac{\partial^2 L_i}{\partial S_i \partial Z_i} < 0\right)$; and (4) the effects vary by household characteristics, such as income levels or the gender of the household.

3. METHODOLOGY

3.1. Data Description

We use multiple data sources to achieve the objectives. The primary data set is the 2018–19 Household Integrated Economic Survey (HIES), conducted by the Pakistan Bureau of Statistics (PBS). This nationally representative survey includes 24,809 households in Pakistan and provides comprehensive data on economic and social indicators at the national and provincial levels, with urban and rural disaggregation (Nawaz, 2021).

Second, we use the Pakistan Mouza Census 2020 to capture village-level road infrastructure. The census, conducted by the Agricultural Census Wing of the Pakistan Bureau of Statistics, covers all Mouzas, the smallest administrative units in rural Pakistan, and collects data on land use, crops, irrigation, livestock, forestry, and the socioeconomic conditions of the population.[2]

Data on natural disasters, such as droughts and earthquakes, and access to road infrastructure, are derived from the Mouza Census 2020.

We used monthly Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) rainfall data to construct the final rainfall measure at the tehsil level, aggregating spatially using tehsil shapefiles. CHIRPS is a satellite-based dataset publicly available for research purposes from 1981 to 2018.[3] For analytical purposes, monthly data covering the period from 1989 to 2018 were aggregated at the tehsil level and

[2]The Mouza Census provides vital information on major crops, sources of irrigation, cultivated areas, natural resources, disasters, and the number of settlements within communities. It also documents socioeconomic indicators, including access to drinking water, electricity, sewerage systems, healthcare, education, veterinary facilities, and sports facilities. In addition, the census captures data on infrastructure, such -as roads and markets, as well as accessibility to police stations, financial institutions, and other services. For further details, see https://www.pbs.gov.pk/content/mouza-census-2020.

[3] For more information; see https://www.chc.ucsb.edu/data/chirps

subsequently merged with HIES data using tehsil identifiers. The tehsil-level identifiers were obtained from the PBS.

3.2. Variable Construction

This employs two different measures to analyse the debt dynamics at the household level:

(1) Debt Take-Up: This study defines an indicator (a binary variable) that captures household borrowing decisions in the past year. If the household borrows, it takes the value 1; otherwise, it takes the value 0. This variable captures the household's decision to borrow and serves as a proxy for credit access (Kandikuppa & Gray, 2022; Churchill, et al. 2023).

(2) Debt Amount: This variable captures total borrowing reported by the household. This measure is in line with the global literature on capturing the financial intensity of borrowing. (Kandikuppa & Gray, 2022; Churchill, et al. 2023).

These two measures capture extensive (decision to borrow) and intensive (amount borrowed) margins of debt, allowing for a comprehensive assessment of borrowing behaviour. This study constructs two variables to analyse the impact of public infrastructure on borrowing patterns among households.

Energy Access Index: First, a composite Energy Access Index (EAI) is constructed using three dimensions of energy-related infrastructure: electricity access, availability of clean water, and safe sanitation. Each component is standardised and centred using the inverse covariance index (Anderson method), which assigns weights based on the components' inverse covariance matrix. The EAI ranges from 0 to 1, with higher values reflecting improved energy service access. The EAI provides comprehensive details on energy infrastructure, as reported in the global literature (Chakravarty & Tavoni, 2013; Sovacool, 2012).

Road Infrastructure: This variable is constructed as a binary indicator of primary road access in the Mouza that is paved (1 = metal-paved, 0 = otherwise). This data is taken from the Pakistan Mouza Census 2020, which provides detailed information on community infrastructure. According to literature, access to paved roads enhances market connectivity, facilitates access to financial and public services, and reduces the economic impacts of climatic shocks (Donaldson, 2018; Jacoby & Minten, 2009; Arif & Iqbal, 2009).

3.3. Estimation Method

This study uses a logistic regression model for borrowing decisions to examine the relationship between public services, climatic shocks, and household borrowing behaviour. Furthermore, a linear regression model is used to analyse debt amounts. This empirical strategy allows to validate the hypotheses developed based on theoretical framework. It also allows to evaluate the direct and interaction effects of climatic shocks and public services on household borrowing dynamics. The borrowing decision (L_i) is captured as a binary outcome, where $L_i = 1$ if a household borrows and $L_i = 0$ otherwise. The corresponding probability of borrowing is estimated using a logistic regression framework:

$$Logit(P(L_i = 1)) = \propto + \beta_1 Z_i + \beta_2 S_i + \beta_3 (Z_i \times S_i) + X_i \Gamma + \mu_r + \nu_p + \epsilon_i,$$

where:

Z_i: Climatic shocks (for example, rainfall anomalies).
S_i: Access to public services, such as energy and roads.
$(Z_i \times S_i)$: Interaction term capturing the mitigating role of public services during shocks.
X_i: Vector of household characteristics, including income, household size, head experience, head gender, and head literacy.
μ_r: Regional fixed effects to account for unobserved heterogeneity at the regional level.
ν_p: Provincial fixed effects to account for province-level factors.
ϵ: Error term that captures unobserved individual-specific factors.
For the debt amount (A_i), we estimate the following linear regression model:

$$A_i = \propto + \beta_1 Z_i + \beta_2 S_i + \beta_3 (Z_i \times S_i) + X_i \Gamma + \mu_r + \nu_p + \epsilon_i,$$

where all variables are defined as above, and Ai represents the inverse hyperbolic sine (IHS) transformed debt amount to address skewness in the data.

We incorporate regional fixed effects (μ_r) and provincial fixed effects (ν_p) in all to control unobserved heterogeneity, ensuring that the estimates of Z_i, S_i, and their interaction are not biased by omitted regional or provincial factors. We also include various household characteristics (X_i) to address individual-level heterogeneity (see Appendix Table A1 for a detailed description of all variables). The interaction term $(Z_i \times S_i)$ which helps us assess whether public services mitigate the financial impact of climatic shocks.

4. RESULTS AND DISCUSSION

This section presents empirical results and discussion aligned with the objectives of the study.

4.1. Baseline Results

The empirical analysis started by estimating baseline regression models. Table 1 presents baseline results showing the impact of household characteristics on the likelihood of household borrowing and per capita debt. Four different specifications are used to ensure the robustness of results. Model 1 captures basic household characteristics, while Model 2 extends the specification by including provincial fixed effects. Model 3 includes regional fixed effects, while Model 4 provides a more fully extended version with both provincial and regional fixed effects.

The empirical results show that household income, measured as log expenditures, is an important factor in shaping borrowing decisions. Table 1 shows that a one-unit increase in income (log expenditures) reduces the probability of borrowing by 46 to 53 percent (odds ratio 0.54 to 0.60) and reduces per capita debt by coefficients from -0.561 to -0.904. This suggests that richer households rely less on loans, possibly due to better financial stability, savings, or access to other resources. On the other hand, larger households are inclined to borrow more. Each additional member increases the likelihood of borrowing by 4.7 to 5.0 percent ($p < 0.01$) and debt amounts ranging from 0.018 to 0.092.

Table 1

Household Debt Dynamics in Pakistan

Variables	Debt Take-up (Odds Ratios)				Debt Amount (Coefficients)			
	1	2	3	4	1	2	3	4
Income	0.543***	0.454***	0.607***	0.471***	-0.756***	-0.904***	-0.561***	-0.857***
	(0.024)	(0.022)	(0.027)	(0.024)	(0.067)	(0.065)	(0.070)	(0.069)
Household Size	1.047***	1.011*	1.050***	1.012*	0.086***	0.018*	0.092***	0.020**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.011)	(0.010)	(0.011)	(0.010)
HH Exp	0.816***	0.696***	0.813***	0.695***	-0.325***	-0.515***	-0.333***	-0.516***
	(0.046)	(0.042)	(0.045)	(0.042)	(0.097)	(0.093)	(0.097)	(0.093)
HH Gender	0.892**	1.325***	0.916	1.335***	-0.219**	0.411***	-0.171*	0.419***
	(0.050)	(0.081)	(0.052)	(0.082)	(0.099)	(0.094)	(0.099)	(0.094)
HH LIT	0.801***	0.771***	0.824***	0.778***	-0.394***	-0.381***	-0.340***	-0.369***
	(0.029)	(0.030)	(0.030)	(0.031)	(0.065)	(0.062)	(0.065)	(0.062)
Wald chi2/F stat	562.18	2,848.54	635.64	2,845.35	94.89	394.08	97.12	354.54
Observations	23,000	23,000	23,000	23,000	23,000	23,000	23,000	23,000
Pro FE Effects	No	Yes	No	Yes	No	Yes	No	Yes
Region FE Effects	No	No	Yes	Yes	No	Yes	No	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parentheses., respectively.

The analysis shows that the age of the head of household, used as a proxy for experience, has a negative impact on the probability of borrowing by the household as well as on the debt amount. Table 1 reveals that one additional year of experience (age) reduces the likelihood of borrowing by 18.4 percent to 30.4 percent (odds ratio 0.69 to 0.82) and lowers debt levels, with coefficients between -0.325 and -0.516. These results indicate that experienced heads can manage financial resources more effectively and diversify their income to rely less on borrowing, especially during a crisis.

The analysis shows that male-headed households are less likely to borrow (odds ratio 0.892, $p < 0.05$) in model 1. Male-headed households are more likely to borrow (odds ratio 1.325, $p < 0.01$) and have higher per capita debt (coefficients of 0.411 to 0.419) when regional fixed effects are included. These differences are important for understanding decision-making about borrowing under different socio-economic and cultural factors.

The literacy head has consistently had a negative impact on the probability of borrowing and debt levels. Table 1 shows that literate households are 18 percent to 23 percent less likely to borrow (odds ratios from 0.771 to 0.824), and their per capita debt is lower, with coefficients from -0.340 to -0.394. This implies that literacy plays an important role in improving financial management.

4.2. Role of Energy, Road, and Rainfall Shocks

This subsection analyses the impact of access to energy and road infrastructure on household debt dynamics, including both the likelihood of borrowing and the amount owed, after controlling for covariates (see Table 2). The Energy Access Index (EAI) is constructed using the Anderson method, which combines clean water, electricity, and safe sanitation. This study finds that access to energy is significantly associated with lower borrowing and smaller debt levels. Table 2 shows that energy access reduces the likelihood of borrowing by 0.794 to 0.876 ($p < 0.01$). This study further finds that energy access has a negative impact on the amount of debt (coefficients ranging from -0.397 to -

0.161, $p < 0.01$). These results indicate that the availability of energy infrastructure reduces financial vulnerability, lowers living costs, and enhances overall resilience.

Table 2

Impact of Energy and Road on Debt Dynamics

Variables	Debt Take-up (Odds Ratios)				Debt Amount (Coefficients)			
	1	2	3	4	1	2	3	4
Energy	0.794***	0.862***	0.847***	0.876***	-0.397***	-0.180***	-0.283***	-0.161***
	(0.023)	(0.029)	(0.026)	(0.031)	(0.051)	(0.049)	(0.053)	(0.052)
Road	0.750***	0.849*	0.838**	0.870	-0.474***	-0.145	-0.299**	-0.116
	(0.064)	(0.076)	(0.073)	(0.080)	(0.120)	(0.106)	(0.122)	(0.110)
Wald chi2/F Stat	659.57	2,832.24	693.82	2,846.23	82.23	325.87	79.96	299.52
Observations	23,000	23,000	23,000	23,000	23,000	23,000	23,000	23,000
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pro FE Effects	No	Yes	No	Yes	No	Yes	No	Yes
Region FE Effects	No	No	Yes	Yes	No	Yes	No	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parentheses., respectively.

Table 2 shows that access to metal-paved roads significantly reduces the likelihood of borrowing (odds ratios ranging from 0.750 to 0.870) and lowers debt levels (coefficients ranging from 0.474 to -0.116). This implies that access to road infrastructure helps diversify and expand income opportunities, reduces time and transaction costs, and enhances market access. This, in turn, implies that it reduces the borrowing requirements. These results depict the transformative role of public infrastructure in overcoming financial stress by providing alternative income opportunities and reducing transaction costs (Donaldson, 2018; Jacoby & Minten, 2009; Arif & Iqbal, 2009).

Table 3 presents the analysis after including rainfall shock as an additional variable. Annual rainfall deviation from long-term averages is used to capture rainfall shocks. This study uses annual rainfall deviation to assess the impact of shocks on household debt. All specifications also include covariates, as in Tables 1 and 2, to ensure robustness. Table 3 shows that rainfall shock is significantly associated with borrowing decisions and borrowing amounts. The results indicate that households are significantly more likely to borrow when rainfall deviates, with odds ratios ranging from 1.039 to 1.656 (mostly $p < 0.01$). These results suggest that climate shocks, such as excessive or insufficient rainfall, adversely affect household incomes, particularly in rural areas where agriculture is the primary source of income and is highly sensitive to such shocks. Table 3 shows that rainfall shock has a positive and significant impact on debt size, with coefficients ranging from 0.931 to 0.938 ($p < 0.01$). These results indicate that rainfall anomalies increase both the likelihood and size of household debt, highlighting the financial stress caused by climate shocks. Overall, these results underline household vulnerability to climatic shocks.

Table 3

Impact of Energy, Road, and Climate on Debt Dynamics

Variables	Debt Take-up (Odds Ratios)				Debt Amount (Coefficients)			
	1	2	3	4	1	2	3	4
Energy	0.884***	0.865***	0.920***	0.880***	-0.219***	-0.177***	-0.153***	-0.156***
	(0.027)	(0.029)	(0.029)	(0.031)	(0.049)	(0.049)	(0.051)	(0.052)
Road	0.829**	0.848*	0.880	0.870	-0.150	-0.144	-0.047	-0.112
	(0.071)	(0.076)	(0.077)	(0.080)	(0.109)	(0.106)	(0.112)	(0.109)
Rain Shock	1.656***	1.039	1.648***	1.041	0.938***	0.067	0.931***	0.070
	(0.021)	(0.027)	(0.021)	(0.027)	(0.023)	(0.045)	(0.023)	(0.045)
Wald chi2/F Stat	1,970.48	2,844.27	1,970.90	2,857.07	289.84	301.48	258.75	278.90
Observations	23,000	23,000	23,000	23,000	23,000	23,000	23,000	23,000
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pro FE Effects	No	Yes	No	Yes	No	Yes	No	Yes
Region FE Effects	No	No	Yes	Yes	No	Yes	No	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parentheses., respectively

4.3. Interaction Effects: Rainfall Shock, Energy Access, and Road Infrastructure

One of the key objectives is to examine the role of infrastructure in moderating the financial impacts of climatic shocks, specifically rainfall anomalies. This study uses interaction terms between rainfall shocks and infrastructure variables, such as energy access and road connectivity, to analyse the moderating impacts. All specifications given in Table 4 include covariates, as in Tables 1 and 2, to ensure robustness. Table 5 presents the interaction effects of rainfall shocks with energy access and road infrastructure on household debt dynamics.

The analysis shows that rainfall shocks have a positive and significant impact, with odds ratios for debt take-up ranging from 1.546 to 1.580 and coefficients for debt amounts ranging from 0.835 to 0.871 ($p < 0.01$). These results align with those presented in Table 3. Households are likely to borrow more and incur more debt when rainfall deviates from long-term averages.

Table 4

Impact of Rainfall Shock Interactions with Energy and Road on Debt Dynamics

Variables	Debt Take-up (Odds Ratios)				Debt Amount (Coefficients)			
	1	2	3	4	1	2	3	4
Rain Shock	1.580***	1.572***	1.553***	1.546***	0.866***	0.871***	0.841***	0.835***
	(0.021)	(0.020)	(0.020)	(0.020)	(0.023)	(0.023)	(0.023)	(0.023)
Energy	0.902**	0.780***	0.928	1.019	0.058	-0.381***	0.107	0.263***
	(0.045)	(0.023)	(0.047)	(0.053)	(0.066)	(0.048)	(0.066)	(0.069)
Energy*Rain	0.931***	—	0.924***	0.917***	-0.251***	—	-0.264***	-0.277***
	(0.017)		(0.017)	(0.017)	(0.031)		(0.031)	(0.031)
Road	0.750***	0.318***	0.302***	0.374***	-0.380***	-0.939***	-1.154***	-0.907***
	(0.063)	(0.068)	(0.063)	(0.077)	(0.110)	(0.158)	(0.158)	(0.159)
Road*Rain	—	1.520***	1.546***	1.468***	—	0.450***	0.516***	0.474***
		(0.119)	(0.120)	(0.111)		(0.103)	(0.102)	(0.101)
Wald chi2/F Stat	1,811.56	1,754.29	1,787.80	1,816.61	263.22	263.64	242.02	221.67
Observations	23,000	23,000	23,000	23,000	23,000	23,000	23,000	23,000
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pro FE Effects	No	Yes	No	Yes	No	Yes	No	Yes
Region FE Effects	No	No	Yes	Yes	No	Yes	No	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parentheses., respectively

Energy access reduces the likelihood of borrowing (odds ratios ranging from 0.780 to 0.928, significant in most models) and the amount of debt (coefficients ranging from -0.381 to 0.263, significant in some cases). The interaction term between the rainfall shock and energy access is significant and negative. For debt take-up, the odds ratios for the interaction term (Energy*Rain) range from 0.917 to 0.931 ($p < 0.01$), and for debt amounts, the coefficients range from -0.251 to -0.277 ($p < 0.01$). Using model 1, the net effect of the rainfall shock on the dynamics of household debt is calculated by combining the direct impact of the rainfall shock, the direct effect of energy access, and their interaction term, using the formula Net Effect = $\beta_{\text{Rain}} + \beta_{\text{Energy}} + \beta_{\text{Energy}*\text{Rain}}$. For debt take-up, the coefficients are $\beta_{\text{Rain}} = 1.580$, $\beta_{\text{Energy}} = 0.902$, and $\beta_{\text{Energy}*\text{Rain}} = 0.931$ (Table 5). Substituting these values, the log odds are ln(1.580)+ln(0.902)+ln(0.931) = 0.283, yielding a net odds ratio of $e^{0.283} \approx 1.327$, which means that the likelihood of borrowing increases by approximately 32.7 percent with energy access. However, without energy access (odds ratio = 1.580), borrowing pressures due to rainfall shocks are significantly higher. The mitigating effect of energy access reduces the likelihood of borrowing $1 - \frac{1.327}{1.580} \approx 16.0\%$. For debt amounts, the coefficients are $\beta_{\text{Rain}} = 0.835$, $\beta_{\text{Energy}} = 0.263$, and $\beta_{\text{Energy}*\text{Rain}} = -0.277$ (Table 4). Substituting these values, the net effect on the per capita debt amount transformed by IHS is 0.835 + 0.263 − 0.277 = 0.821. To interpret this in monetary terms, the net effect is multiplied by the mean per capita debt of PKR 5509, resulting in an increase of approximately PKR 4521. This indicates that rainfall shocks, moderated by energy access, increase the per capita debt by 4521 PKR. However, the negative interaction term ($\beta_{\text{Energy}*\text{Rain}} = -0.277$) indicates that energy access mitigates the overall debt burden relative to scenarios without adequate energy infrastructure. Without energy access, the financial impact of rainfall shocks on debt amounts would be significantly higher.

Table 5

Impact of Rainfall Shock, Energy Access, and Road Infrastructure on Debt Dynamics

Infrastructure	Outcome	βRain	βInfra	βInfra*Rain	Net Effect
Energy Access	Debt Take-Up (Odds Ratios)	1.580	0.902	0.931	0.283 (Log Odds)
	Debt Amount (Coefficients)	0.835	0.263	-0.277	0.821
Road Infrastructure	Debt Take-Up (Odds Ratios)	1.572	0.849	1.520	0.426 (Log Odds)
	Debt Amount (Coefficients)	0.871	-0.939	0.450	0.382

Note: Author's own estimation based on Table 4.

Road infrastructure alone shows mixed effects. It reduces debt take-up (odds ratios from 0.302 to 0.750) and debt amounts (coefficients from -0.907 to -0.380), though its effects are less robust than those of energy access. However, the interaction term between the rainfall shock and road infrastructure (Road*Rain) reveals a significant positive association with both debt take-up (odds ratios ranging from 1.468 to 1.546) and debt amounts (coefficients of 0.450 to 0.516, $p < 0.01$). Using model 2, the net effect of the rainfall shock on household debt dynamics is calculated by combining the direct impact of the rainfall shock, the direct effect of road infrastructure, and their interaction term. For debt take-up, the coefficients are $\beta_{\text{Rain}} = 1.572$, $\beta_{\text{Road}} = 0.849$, and $\beta_{\text{Road}*\text{Rain}} = 1.520$ (Table 4). Substituting these values, the log odds are ln(1.572) + ln(0.849) + ln(1.520) = 0.426, resulting in a net odds ratio of $e^{0.426} \approx 1.531$, which means that the likelihood of borrowing increases by approximately 53. 1 percent with the road infrastructure. However, without road infrastructure (odds ratio = 1.572), borrowing pressures due to rainfall shocks remain higher. For debt amounts, the coefficients are $\beta_{\text{Rain}} = 0.871$, $\beta_{\text{Road}} = -0.939$, and $\beta_{\text{Road}*\text{Rain}} = 0.450$ (Table 4). Substituting these values, the net effect on the per capita debt amount transformed by IHS is 0.871 − 0.939 + 0.450 = 0.382. To

interpret this in monetary terms, the net effect is multiplied by the mean per capita debt of PKR 5509, increasing approximately PKR 2105.

This analysis shows that rainfall shocks, moderated by road infrastructure, increase per capita debt by PKR 2105. The positive sign of the interaction term ($\beta_{\text{Road*Rain}} = 0.450$) indicates that access to road infrastructure increases the financial impact of rainfall shocks. One possible reason for this outcome is that it might increase by allowing access to credit and market connectivity. Although the direct negative effect of access to road infrastructure ($\beta_{\text{Road}} = -0.939$) partially offsets this increase, it reflects the dual role of road infrastructure in both reducing baseline debt levels and increasing borrowing during climatic shocks. Table 5 shows the impact of Rainfall shock, energy Access, and road infrastructure on debt dynamics. The net effects calculated are based on Table 4.

4.4. Heterogeneity Analysis

This section extends the analysis by analysing the moderating effects across two key dimensions: (i) poverty status, where households are divided based on income profile and categories as poor and non-poor, and (ii) the gender of the household head, where the sample is split into male-headed vs female-headed. The empirical reveals distinct patterns in the impact of rainfall shocks, energy access, and road infrastructure on debt dynamics across poor and non-poor households.

Table 6 shows that rainfall shocks significantly increase the likelihood of borrowing for both groups, with odds ratios of 1.622 ($p < 0.01$) for non-poor households and 1.770 ($p < 0.01$) for poor households, indicating greater financial vulnerability among the poor. The empirical results regarding Energy Access Index (EAI) show that energy access reduces the likelihood of borrowing, with odds ratios of 0.900 ($p < 0.01$) for nonpoor households and 0.792 ($p < 0.01$) for poor households, reflecting the critical role of energy infrastructure in buffering financial shocks, particularly for the poor.

Similarly, access to road infrastructure reduces the likelihood of borrowing, with odds ratios of 0.851 ($p < 0.10$) for non-poor households and 0.679 ($p < 0.05$) for poor households, highlighting a stronger alleviating effect of connectivity on vulnerable groups. The analysis further shows that energy access has negative coefficients of -0.193 ($p < 0.01$) for non-poor households and -0.407 ($p < 0.01$) for poor households, while road infrastructure shows coefficients of -0.131 ($p > 0.10$) and -0.601 ($p < 0.05$) for debt amount, respectively. These results indicate that access to infrastructure significantly stabilises finances, with greater reductions in borrowing observed among poor households.

Table 6

Heterogeneous Analysis: Poverty Status

Variables	Debt Take-up (Odds Ratios)		Debt Amount (Coefficients)	
	Non-poor	Poor	Non-poor	Poor
Energy	0.900***	0.792***	-0.193***	-0.407***
	(0.031)	(0.049)	(0.055)	(0.107)
Road	0.851*	0.679**	-0.131	-0.601**
	(0.081)	(0.124)	(0.117)	(0.298)
Rain Shock	1.622***	1.770***	0.866***	1.227***
	(0.024)	(0.048)	(0.025)	(0.050)
Wald chi2/F Stat	1,433.31	486.45	201.54	86.70
Observations	18,554	4,446	18,554	4,446
Covariates	Yes	Yes	Yes	Yes
Pro FE Effects	Yes	Yes	Yes	Yes
Region FE Effects	Yes	Yes	Yes	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parenthesis., respectively.

The gender-based analysis of debt dynamics reveals distinct patterns in how rainfall shocks, energy access, and road infrastructure affect borrowing behavior and debt levels for male- and female-headed households. For debt take-up, rainfall shocks significantly increase the likelihood of borrowing for both groups, with odds ratios of 1.635 ($p < 0.01$) for male-headed households and 1.794 ($p < 0.01$) for female-headed households, indicating slightly higher vulnerability among female heads. Energy access reduces the likelihood of borrowing for both groups, with an odds ratio of 0.891 ($p < 0.01$) for male-headed households and 0.864 ($p > 0.10$) for female-headed households, though the effect is more pronounced and significant for male-headed households. Road infrastructure has a significant positive impact on borrowing among male-headed households (odds ratio 0.796, $p < 0.05$), whereas for female-headed households, the effect is positive but not statistically significant (odds ratio 1.377, $p > 0.10$) (Table 7). For debt amounts, rainfall shocks again have a significant positive impact, with coefficients of 0.920 ($p < 0.01$) for male-headed households and 1.028 ($p < 0.01$) for female-headed households, suggesting higher debt burdens for female-headed households during rainfall anomalies. Energy access reduces debt amounts for both groups, with coefficients of -0.197 ($p < 0.01$) for male-headed households and -0.358 ($p < 0.05$) for female-headed households, indicating that access to energy infrastructure provides stronger financial stability for female-headed households. Road infrastructure reduces debt for male-headed households (–0.209, $p < 0.10$), while its effect on female-headed households is positive but not statistically significant (0.542, $p > 0.10$).

Table 7

Heterogeneous Analysis: Gender of Household Head

Variables	Debt Take-up (Odds Ratios)		Debt Amount (Coefficients)	
	Female Head	Male Head	Female Head	Male Head
Energy	0.864	0.891***	-0.358**	-0.197***
	(0.089)	(0.028)	(0.159)	(0.052)
Road	1.377	0.796**	0.542	-0.209*
	(0.447)	(0.071)	(0.441)	(0.113)
Rain Shock	1.794***	1.635***	1.028***	0.920***
	(0.080)	(0.022)	(0.069)	(0.024)
Wald chi2/F Stat	295.23	1,676.44	60.69	274.55
Observations	2,208	20,792	2,208	20,792
Covariates	Yes	Yes	Yes	Yes
Pro FE Effects	Yes	Yes	Yes	Yes
Region FE Effects	Yes	Yes	Yes	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parenthesis., respectively.

4.5. Robustness

This study extends the analysis by investigating the impact of an alternative proxy for climate shocks to establish robustness. It employs drought and earthquake events at the tehsil level, generated from the MOUZA Census 2020. The MOUZA Census 2020 provides self-reported shocks at the mouza level. These variables provide information on the impacts of different shocks across various environmental stressors, mainly drought and earthquakes. The analysis presented in Table 8 confirms that the impacts of climatic shocks on debt dynamics are consistent across alternative proxies for environmental stressors, namely self-reported drought and earthquake events.

The results show that both drought and earthquake shocks significantly increase the likelihood of borrowing, with odds ratios of 1.880 ($p < 0.01$) and 4.640 ($p < 0.01$) for debt take-up, respectively. This indicates that households are more likely to rely on loans in response to both types of shocks, with earthquakes showing a particularly pronounced effect. Similarly, for debt amounts, both drought and earthquake shocks significantly increase borrowing levels, with

coefficients of 0.751 ($p < 0.01$) for drought and 3.050 ($p < 0.01$) for earthquakes, highlighting the financial strain these events impose (Table 8). These results show the robustness of the findings.

Table 8

Robustness Analysis: Impact of Drought and Earthquake on Debt Dynamics

Variables	Debt Take-up (Odds Ratios)		Debt Amount (Coefficients)	
	Drought	Earthquake	Drought	Earthquake
Energy	0.902***	0.898***	-0.125**	-0.127**
	(0.032)	(0.032)	(0.052)	(0.052)
Road	0.894	0.915	-0.054	-0.055
	(0.083)	(0.083)	(0.111)	(0.110)
Shock	1.880***	4.640***	0.751***	3.050***
	(0.197)	(0.758)	(0.137)	(0.276)
Wald chi2/F Stat	2,842.20	2,909.03	282.03	316.01
Observations	23,000	23,000	23,000	23,000
Covariates	Yes	Yes	Yes	Yes
Pro FE Effects	Yes	Yes	Yes	Yes
Region FE Effects	Yes	Yes	Yes	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parenthesis., respectively.

Following the literature, we also use the debt-to-income ratio as an alternative measure of borrowing to establish the robustness of the results (Churchill, et al. 2023; Kasoga & Tegambwage, 2021; Schicks, 2014; Chichaibelu & Waibel, 2017). The findings using the debt-to-income ratio as an outcome variable closely align with the results of the debt take-up and per capita debt amount analyses presented earlier (Table 9). Energy access and road infrastructure consistently show a negative relationship with the debt-to-income ratio, while rainfall shocks, as expected, significantly increase it (Table 9).

Table 9

Impact of Rainfall Shock, Energy, and Road on Debt Dynamics: Alternative Measure

Variables	Debt Take-up (Odds Ratios)		Debt Amount (Coefficients)	
	Drought	Earthquake	Drought	Earthquake
Energy	-0.060***	-0.044***	-0.036***	-0.032***
	(0.010)	(0.010)	(0.010)	(0.011)
Road	-0.061***	-0.057**	-0.028	-0.040*
	(0.023)	(0.023)	(0.024)	(0.023)
Shock	0.169***	0.011	0.168***	0.013
	(0.005)	(0.009)	(0.005)	(0.009)
Wald chi2/F Stat	200.63	217.93	178.02	199.55
Observations	23,000	23,000	23,000	23,000
Covariates	Yes	Yes	Yes	Yes
Pro FE Effects	No	Yes	No	Yes
Region FE Effects	No	No	Yes	Yes

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parenthesis., respectively.

4.6. Dealing with Endogeneity

The relationship between energy access and household debt may be confounded by endogeneity arising from unobserved factors that simultaneously influence energy access and borrowing behaviour (Nawaz, 2021; Churchill, et al.2022; Churchill & Smyth, 2021). Nawaz (2021) & Zhang, et al. (2021) suggest using the Lewbel (2012) approach to address endogeneity issues, particularly when instruments are weak. Building on this

framework, we implement the two-stage least squares (2SLS) method of Lewbel (2012), incorporating both external and internally generated instrumental variables (IVs) to mitigate endogeneity. We use community-level media exposure as a novel and justified instrument in this context. Media penetration often reflects external investments in communication infrastructure, which are unlikely to directly affect individual household borrowing decisions. However, it indirectly influences energy access by increasing awareness and demand for community-level infrastructure improvements. Using this approach, we estimate the impact on debt take-up, debt amount, and debt-to-income ratio. The results are presented in Table 10. The Cragg-Donald weak-identification Wald test confirms the validity of the proposed instrument (Jiang & Lyu, 2019; Desbordes & Verardi, 2012), and the overidentification tests (Sargan statistics) confirm the instrument exogeneity (Table 10). These results ensure that the instruments are uncorrelated with the error term, a key requirement for IV validity. The results demonstrate the significant impact of energy access on household debt indicators. We have seen that energy access and road infrastructure reduce debt take-up, per capita debt, and the debt-to-income ratio, while rain shock increases them (Table 10). These results are in line with earlier findings.

Table 10

Instrumental Variable (IV) Regression Results

	Std IV	Gen Inst	Gen Ext Inst
Panel A: Debt Take Up)			
Energy	-0.065***	-0.554***	-0.085***
	(0.016)	(0.096)	(0.016)
Road	-0.016	0.100***	-0.011
	(0.012)	(0.027)	(0.012)
Rain Shock	0.093***	0.095***	0.093***
	(0.002)	(0.002)	(0.002)
Constant	0.073***	0.064***	0.073***
	(0.004)	(0.006)	(0.004)
Observations	23,000	23,000	23,000
Cragg-Donald F-stat	1811.351	37.236	629.072
Overidentification Test (p-value)	–	0.0445	0.0000
Panel B: Per Capita Debt			
Energy	-0.472***	-4.672***	-0.644***
	(0.162)	(0.913)	(0.159)
Road	-0.226*	0.769***	-0.185
	(0.126)	(0.259)	(0.126)
Rain Shock	0.958***	0.972***	0.959***
	(0.019)	(0.022)	(0.019)
Constant	0.695***	0.620***	0.692***
	(0.043)	(0.053)	(0.043)
Observations	23,000	23,000	23,000
Cragg-Donald F-stat	1811.351	37.236	629.072
Overidentification Test (p-value)	–	0.0459	0.0000

Note: Author's own estimation. *** p<0.01, ** p<0.05, * p<0.10. Robust S.E. in parenthesis., respectively. StdIV means Standard IV, GenInst means IV with Generated Instruments only, and GenExtInst means IV with Generated Instruments and External Instruments.

5. CONCLUDING REMARKS AND POLICY LESSONS

This study offers key insight into the dynamics of household debt in Pakistan, with a focus on the interaction among climatic shocks, public infrastructure, and borrowing behaviour. The empirical findings indicate that access to public infrastructure plays a key role in mitigating financial vulnerabilities stemming from environmental stressors. The results

show that climatic shocks, such as rainfall shocks, significantly increase the likelihood of borrowing and the amount of debt. By contrast, access to energy infrastructure significantly reduces the probability of borrowing and the amount of debt. Road infrastructure has a dual role: it reduces borrowing overall but increases borrowing during climatic shocks. The analysis of heterogeneity indicates that poor and female-headed households are heavily impacted by climatic shocks and tend to rely more on borrowing. Access to public infrastructure, especially energy access, is crucial in stabilising vulnerable populations by easing financial pressures and enhancing resilience. These insights carry important implications for infrastructure investment and disaster management policies in Pakistan.

The analysis presented in this paper highlights key areas for policy intervention to overcome financial vulnerabilities and improve well-being. First, access to energy infrastructure for all is a key factor to stabilise income vulnerabilities. Expansion of these facilities, especially in rural areas, should be given top priority by provincial governments. Second, improved local road infrastructure, especially its access, helps to address debt vulnerabilities at the household level.

Addressing regional disparities is essential, especially as provinces like Balochistan and Sindh face major climate and economic vulnerabilities. Implementing targeted interventions such as improving infrastructure and disaster risk management in these areas can help narrow the resilience gap. Additionally, integrating financial services into climate adaptation policies is vital for providing households with alternative safety nets. Expanding access to microfinance, affordable insurance, and emergency relief funds can lessen borrowing pressures during climate shocks, allowing households to recover more effectively and sustainably. These policy measures will enable Pakistan to develop a more resilient and equitable socioeconomic system capable of handling the impacts of climate change.

REFERENCES

Acosta, A., Nicolli, F., and Karfakis, P. (2021). Coping with climate shocks: The complex role of livestock portfolios. *World Development*, 146:105546.

Adnan, M., Xiao, B., Bibi, S., Xiao, P., Zhao, P., &Wang, H. (2024). Addressing current climate issues in Pakistan: An opportunity for a sustainable future. *Environmental Challenges*, page 100887.

Aggarwal, R. (2021). Impacts of climate shocks on household consumption and inequality in India. *Environment and Development Economics*, *26*(5-6):488–511.

Aggarwal, S. (2018). Do rural roads create pathways out of poverty? evidence from India. *Journal of Development Economics*, 133:375–395.

Akbar, M., Abdullah, Naveed, A., & Syed, S. H. (2022). Does an improvement in rural infrastructure contribute to alleviate poverty in Pakistan? A spatial econometric analysis. *Social Indicators Research*, 162(1):475–499.

Alem, Y., Hassen, S., & K¨ohlin, G. (2023). Decision-making within the household: The role of division of labour and differences in preferences. *Journal of Economic Behavior & Organization*, 207:511–528.

Amare, M., Shiferaw, B., Takeshima, H., & Mavrotas, G. (2021). Variability in agricultural productivity and rural household consumption inequality: Evidence from Nigeria and Uganda. *Agricultural Economics*, *52*(1):19–36.

Arif, G. & Iqbal, N. (2009). Infrastructure and poverty nexus: The case of rural Pakistan. In Mohammad, I. & Yasin, H., editors, *Socioeconomic Challenges Faced by Pakistan*, pages 261–278. International Islamic University, Islamabad, Pakistan.

Arif, G. M., Iqbal, N., & Farooq, S. (2015). Poverty and Pakistan's 2010 flood. In Sinha, A., Bauer, A., & Bullen, P., editors, *The Environments of the Poor in South Asia: Simultaneously Reducing Poverty, Protecting the Environment, and Adapting to Climate Change*, pages 169–190. Oxford University Press, Oxford.

Arora, A. & Birwal, D. (2017). Natural calamities, crop losses and coping strategies: an economic analysis from Odisha. *Indian Journal of Agricultural Economics*, 72(3):385–395.

Barua, S. & Banerjee, A. (2020). Impact of climatic shocks on household well-being: Evidence from rural Bangladesh. *Asia-Pacific Journal of Rural Development*, 30(1-2):89– 112.

Bazilian, M. & Pielke, R. (2013). Making energy access meaningful. *Issues in Science and technology*, 29(4):74–78.

Becchetti, L., Mancini, S., & Savastano, S. (2024). Exposure to climate shocks, poverty and household well-being. *Environment and Development Economics*, pages 1–30.

Carter, C., Cui, X., Ghanem, D., & M´erel, P. (2018). Identifying the economic impacts of climate change on agriculture. *Annual Review of Resource Economics*, *10*(1):361–380.

Chakravarty, S. & Tavoni, M. (2013). Energy poverty alleviation and climate change mitigation: Is there a trade off? *Energy Economics*, 40: S67–S73.

Chichaibelu, B. B. & Waibel, H. (2017). Borrowing from "PUI" to pay "pom": Multiple borrowing and over-indebtedness in rural Thailand. *World Development*, 98:338–350.

Churchill, S. A. & Smyth, R. (2021). Energy poverty and health: Panel data evidence from Australia. *Energy Economics*, 97:105219.

Churchill, S. A., Smyth, R., & Trinh, T.-A. (2022). Energy poverty, temperature and climate change. *Energy Economics*, 114:106306.

Churchill, S. A., Trinh, T.-A., & Danquah, M. (2023). Temperature, climate change, and household financial Behaviour: Evidence from Vietnam. WIDER Working Paper 2023/95, United Nations University World Institute for Development Economics Research (UNU-WIDER), Helsinki, Finland.

Deaton, A. (1992). *Understanding consumption*. Oxford University Press.

Deaton, A. & Muellbauer, J. (1980). *Economics and consumer behaviour*. Cambridge University Press.

Dercon, S. (2004). Growth and shocks: evidence from rural Ethiopia. In *Macroeconomic Policies and Poverty*, pages 308–329. Routledge.

Desbordes, R., & Verardi, V. (2012). A robust instrumental-variables estimator. *The Stata Journal*, *12*(2), 169-181.

Dinkelman, T. (2011). The effects of rural electrification on employment: New evidence from South Africa. *American Economic Review*, *101*(7):3078–3108.

Donaldson, D. (2018). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review*, *108*(4-5):899–934.

Gambo, J., Roslan, S. N. A. B., Shafri, H. Z. M., Ya, N. N. C., & Yusuf, Y. A. (2024). Unveiling and modelling: Land degradation, poverty nexus in Nigeria's semi-arid (Jigawa State) using cloud-based geospatial data. *Journal of Arid Environments*, 222:105151.

Gertler, P. J., Gonzalez-Navarro, M., Gra˘cner, T., and Rothenberg, A. D. (2024). Road maintenance and local economic development: Evidence from Indonesia's highways. *Journal of Urban Economics*, 143:103687.

GoP (2023). Economics survey of Pakistan 2022-23: Annexure - iii Pakistan floods 2022 impact assessment. Ministry of Finance, Government of Pakistan, Islamabad, Pakistan.
https://finance.gov.pk/survey/chapters_23/Annex_III_Pakistan_Floods_2022.pdf. Accessed: 2024-10-06.

Hirvonen, K. (2016). Temperature changes, household consumption, and internal migration.

Hyder, A. & Iqbal, N. (2016). Socio-economic losses of flood and household's coping strategies: Evidence from flood prone district of Pakistan. Technical Report 2016:142, Pakistan Institute of Development Economics.

IPCC (2014). Rural areas. In Field, C. B., Barros, V. R., Dokken, D. J., Mach, K. J., Mastrandrea, M. D., Bilir, T. E., Chatterjee, M., Ebi, K. L., Estrada, Y. O., Genova, R. C., Girma, B., Kissel, E. S., Levy, A. N., MacCracken, S., Mastrandrea, P. R., and White, L. L., editors, *Climate Change 2014 – Impacts, Adaptation and Vulnerability: Part A: Global and Sectoral Aspects: Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, chapter Rural Areas, pages 613–658. Cambridge University Press, Cambridge.

IPCC (2023). *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge.

Jacoby, H. G. (2000). Access to markets and the benefits of rural roads. *The Economic Journal*, 110(465):713–737.

Jacoby, H. G. & Minten, B. (2009). On measuring the benefits of lower transport costs. *Journal of Development Economics*, 89(1):28–38.

Javed, S. A., Ali, W., & Baig, I. (2019). *Household debt in Pakistan: conflict, borrowing, and structural indebtedness*. SLRC Working Paper 86. London: Secure Livelihoods Research Consortium.

Jayachandran, S. (2006). Selling labour low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy*, *114*(3):538–575.

Jiang, Z., & Lyu, K. (2019). Reanalysis of Empirical Research for Return to Schooling: a Weak Instrument Variable Problem.

Kanagawa, M. & Nakata, T. (2008). Assessment of access to electricity and the socioeconomic impacts in rural areas of developing countries. *Energy Policy*, *36*(6):2016–2029.

Kandikuppa, S. & Gray, C. (2022). Climate change and household debt in rural India. *Climatic Change*, *173*(3-4):20.

Kasoga, P. S. and Tegambwage, A. G. (2021). An assessment of over-indebtedness among microfinance institutions' borrowers: The Tanzanian perspective. *Cogent Business & Management*, 8(1):1930499.

Khan, K., Khan, M., Parveen, T., & Hussain, S. (2021). Impacts of climate change in vulnerable communities in Sindh, Pakistan: Voices from the community. *Population Council Working Paper*.

Khandker, S. R., Bakht, Z., & Koolwal, G. B. (2009). The poverty impact of rural roads: Evidence from Bangladesh. *Economic Development and Cultural Change*, *57*(4):685–722.

Kurosaki, T. (2015). Vulnerability of household consumption to floods and droughts in developing countries: evidence from Pakistan. *Environment and Development Economics*, 20(2):209–235.

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

Mukherjee, M. & Fransen, S. (2024). Exploring migration decision-making and agricultural adaptation in the context of climate change: A systematic review. *World Development*, 179:106600.

Nawaz, S. (2021). Energy poverty, climate shocks, and health deprivations. *Energy Economics*, 100:105338.

Nawaz, S. & Mangla, I. U. (2021). The economic geography of infrastructure in Asia: The role of institutions and regional integration. *Research in Transportation Economics*, 88:101061.

Nawaz, S., Anwar, S., & Iqbal, N. (2021). The spatial effects of road infrastructure on employment in Pakistan. *The Pakistan Development Review*, *60*(3):309–330.

Premand, P. & Stoeffler, Q. (2022). Cash transfers, climatic shocks and resilience in the Sahel. *Journal of Environmental Economics and Management*, 116:102744.

Schicks, J. (2014). Over-indebtedness in microfinance–an empirical analysis of related factors on the borrower level. *World development*, 54:301–324.

Shah, A. A., Ye, J., Abid, M., Khan, J., & Amir, S. M. (2018). Flood hazards: household vulnerability and resilience in disaster-prone districts of Khyber Pakhtunkhwa province, Pakistan. *Natural Hazards*, 93:147–165.

Sovacool, B. K. (2012). The political economy of energy poverty: A review of key challenges. *Energy for Sustainable Development*, *16*(3):272–282.

Trinh, T. A. (2018). The impact of climate change on agriculture: findings from households in Vietnam. *Environmental and Resource Economics*, *71*(4):897–921.

Van Vuuren, D. P. & Carter, T. R. (2014). Climate and socio-economic scenarios for climate change research and assessment: Reconciling the new with the old. *Climatic Change*, 122:415–429.

Waqas, M., Naseem, A., Humphries, U. W., Hlaing, P. T., Shoaib, M., & Hashim, S. (2025). A comprehensive review of the impacts of climate change on agriculture in Thailand. *Farming System*, page 100114.

World Bank (2024). Pakistan–Climate Vulnerability. Climate Change Knowledge Portal.

Zappala`, G. (2024). Adapting to climate change accounting for individual beliefs. *Journal of Development Economics*, 169:103289.

Zhang, Q., Appau, S., & Kodom, P. L. (2021). Energy poverty, children's wellbeing and the mediating role of academic performance: Evidence from China. *Energy Economics*, 97:105206.

APPENDIX

APPENDIX A1: VARIABLE DEFINITIONS

Appendix Table A1: Variable Definitions

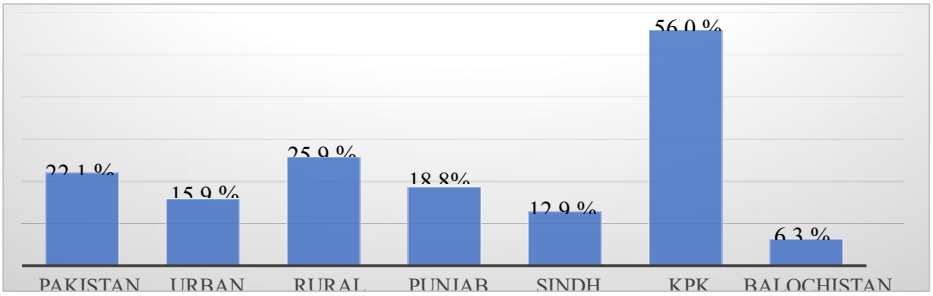
Variables	Descriptions	Sources
Household Size	The total number of individuals living in the household, including all family members and dependents, regardless of their age or economic contribution (Continuous)	HIES
HH EXP	The age (in years) of the head of the household is used to measure experience (continuous – years)	
HH Gender	A binary variable indicating the gender of the household head, where 1 = Male and 0 = Female.	HIES
HH Lit	A binary variable indicating whether the household head is literate, where 1 = Literate and 0 = Illiterate.	HIES
Clean Water	A binary variable indicating access to clean water. Takes the value 1 if the household has access to piped water or water from a hand pump; 0 otherwise.	HIES
Safe Sanitation	A binary variable for access to safe toilet facilities. Takes the value 1 if the household has a flush toilet connected to a public sewerage system, a pit, or an open drain; 0 otherwise.	HIES
Electricity	A binary variable for access to electricity. Takes the value 1 if the household has an electricity connection; 0 otherwise.	HIES
Energy Access	Aggregates three energy-related facilities, including clean water, access to electricity, and safe sanitation. Standardized and aggregated using an inverse covariance index. Energy Access Index is constructed using the Anderson method [ICW INDEX], which involves standardizing and centering variables before computing the index based on the inverse covariance matrix.	Index, HIES
Road	Indicates whether roads in the MOUZA are metal-paved (coded as 1 if yes, 0 otherwise).	MOUZA Census
Rain shock	Rainfall shock is defined as the absolute deviation of annual rainfall from its long-term mean values and is expressed as Rainfall Shock = $\lvert x - \bar{x} \rvert$, where x is the rainfall value for 2018 and $\bar{x}$ is the average rainfall over the last 30 years, constructed at the tehsil level.	CHIRPS
Drought	A continuous variable representing the mean value of drought experienced by MOUZA within a tehsil in the last five years.	MOUZA Census
Earthquakes	A continuous variable representing the mean value of earthquakes experienced by MOUZA within a tehsil in the last five years.	MOUZA Census
Media Access	Aggregates four media facilities, including Radio, TV, Cable, and Newspaper. Standardized and aggregated using an inverse covariance index. Media Access Index is constructed using the Anderson method [ICW INDEX], which involves standardizing and centering variables before computing the index based on the inverse covariance matrix.	Index, MOUZA Census

Notes: Author's formulation.

APPENDIX A2: HOUSEHOLD DEBT DYNAMICS

Household debt plays a key role in the socioeconomic landscape of Pakistan, reflecting financial stress to fulfil both consumption and investment needs. The analysis shows that about 22 percent of households use loans, indicating widespread reliance across the population. Rural households (26 percent) are more likely to borrow than urban ones (16 percent). As shown in Figure 1, borrowing rates vary significantly between provinces, with Khyber Pakhtunkhwa (KP) having the highest and Balochistan the lowest, highlighting regional differences in borrowing behaviours. These variations reflect underlying socioeconomic and infrastructural factors that influence household debt patterns in Pakistan.

Appendix Figure A1: Percentage of Households Involved in Borrowing



Notes: Author's calculation based on the Household Integrated Economic Survey (HIES) 2018-19 data, which is nationally representative. The outcome variable "Loan Taken" is a binary variable, assigned a value of 1 if a loan has been taken by the household and 0 otherwise.

Table A2 presents the distribution of household-level debt in Pakistan. Debt is calculated using information from the Household Integrated Economic Survey (HIES) 2018-19, adjusted for 2023 conditions. Debt amounts are adjusted for inflation using annual inflation rates. The total number of households reported in the 2023 Census (38.3 million) is used to construct the national-level debt estimate. Simulated debt amounts are disaggregated across groups.

This study shows that 22.1 percent of households report borrowing, with an average debt of PKR 72,158 per household and a total debt of PKR 2,767 billion (Table A2). At the provincial level, Khyber Pakhtunkhwa (KP) has the highest borrowing percentage (56.0 percent) and total debt (PKR 1,278 billion), while Balochistan has the lowest borrowing percentage (6.3 percent) and total debt (PKR 27 billion). Rural households are more likely to borrow than urban households, contributing PKR 1,859 billion and PKR 898 billion to total debt, respectively. Across income groups, borrowing is most prevalent among the poorest households (30.4 percent) and least common among the wealthiest (12.3 percent) (Table A2).

Appendix Table A2: Distribution of Household Debt in Pakistan

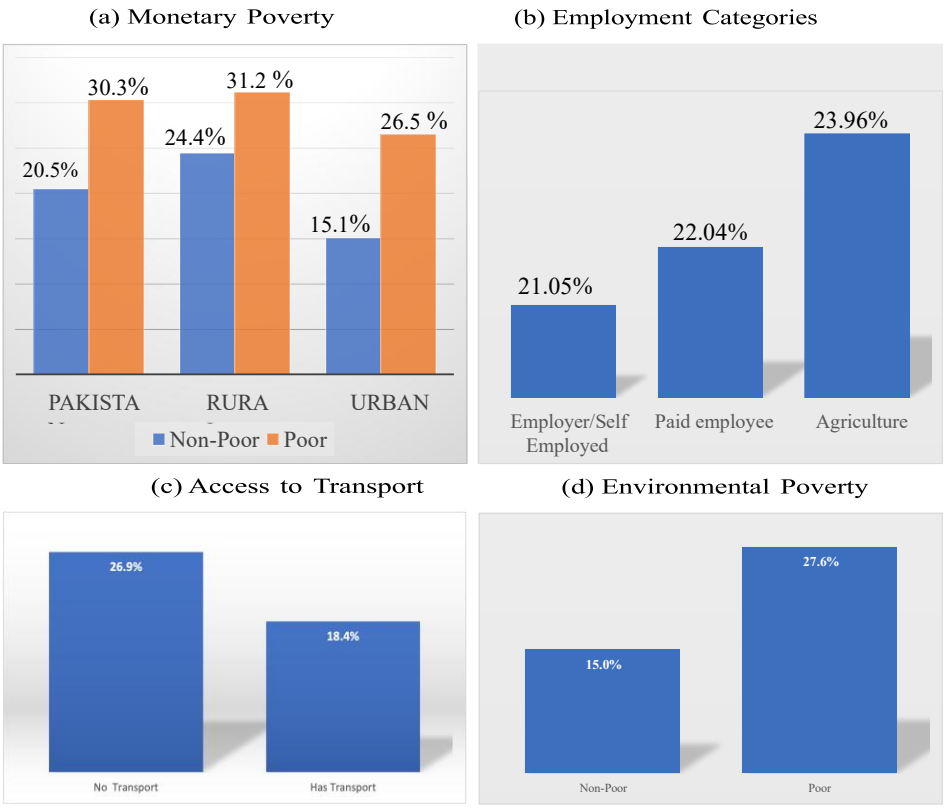
Unit of Analysis	HH in debt (%)	Mean Debt	Number of HHs	Total Debt
Pakistan	22.1%	72158	3834056	2767
Province KP	56.0%	217246	5883007	1278
Punjab	18.8%	60431	2026742	1225
Sindh	12.9%	24510	9871620	242
Balochistan	6.3%	11843	2318519	27
Region Rural	25.9%	79778	23300079	1859
Urban	15.9%	59722	15040487	898
Income Group Poorest (Bottom 20%)	30.4%	74942	7668113	575
2nd	26.7%	77211	7668113	592
3rd	24.3%	73587	7668113	564
4th	19.4%	66963	7668113	513
Richest (Top 20%)	12.3%	69311	7668113	531

Note: Author's calculation based on the Household Integrated Economic Survey (HIES) 201819 data. The total debt at the household level is scaled to the national level by adjusting for inflation as reported by the State Bank

of Pakistan. The population and total household estimates are based on the 2023 Census, with 241.5 million individuals and 38.3 million households.

Appendix Figure A2 shows borrowing patterns across different socioeconomic groups. Poor households are more prone to take loans, as shown in Figure 2A, and those working in informal sectors also depend more on debt, as illustrated in Figure 2B. Households with fewer assets, such as lacking personal transportation, tend to borrow more (Figure 2C) and households that lack access to adequate environmental services, labeled as environmentally deprived, also show a higher tendency to take out loans (Figure 2D).

Appendix Figure A2: Distribution of Household Debt Across Various Socioeconomic Dimensions



Notes: Author formulation based on HIES 2018-19 data.