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Investigating resilience of refugee households in Jordan

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HIGHLIGHTS

- We estimate refugee household resilience in Jordan using quarterly UNHCR data for 2022, combining income and expenditure indicators against normative thresholds.
- Resilience is systematically higher in wealthier and less densely populated governorates but declined on average over the course of 2022.
- Syrian households and those residing outside Amman exhibit lower resilience compared to other groups.
- Cash assistance shows a robust positive contemporaneous association with resilience, particularly among more dependent and vulnerable households.

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ABSTRACT

As of 2024, Jordan hosts over 1.3 million refugees—one of the highest refugee-to-host population ratios globally—posing significant challenges for sustaining refugee household livelihoods. To inform effective support strategies, this study quantifies household resilience using quarterly UNHCR data from 2022. We conceptualize resilience as the ability to maintain a minimum, normatively defined level of well-being when exposed to potential stressors. We focus on two core welfare indicators (real per-capita income and expenditure) and extend existing approaches by estimating the joint conditional probability that both indicators remain above defined normative thresholds. We further examine how resilience relates to dependence on unconditional cash assistance using household panel data with fixed effects, a framework designed to account for unobserved heterogeneity and mitigate targeting bias. Results show that: (i) resilience is higher in wealthier and less densely populated Governorates; (ii) average resilience declined across the four quarters of year 2022; (iii) lower resilience is observed among Syrian households and those residing outside Amman; and (iv) assistance displays a robust contemporaneous positive association with resilience, especially among more dependent and vulnerable households. Although primarily descriptive, these patterns offer indicative insights for refining targeting strategies and designing resilience-oriented social protection programs in protracted displacement settings.

1. Introduction

Since the outbreak of the Syrian civil war in 2011, the Hashemite Kingdom of Jordan (Jordan, henceforth) has faced a significant influx of (mostly Syrian) refugees, with numbers increasing sharply since 2013 (Alrababa'h et al., 2021; Francis, 2015). As of 2023, the United Nations High Commissioner for Refugees (UNHCR) estimates that between 700,000 and 1.3 million refugees reside in Jordan, comprising 7% to 11% of the total population. They are predominantly from Syria, with smaller groups from Iraq, Yemen, Sudan, and Somalia, making Jordan the second highest per capita refugee-hosting country globally (UNHCR, 2018). The direct cost of the refugee crisis to Jordan since 2011 has been estimated at about USD 11 billion, covering expenditures on education, health, water, energy, sanitation, and other essential services (Rosshandler, 2019).

While much of the existing literature has emphasized the economic and social impacts of forced displacement on host communities,[1]

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[1] See, *inter alia*, Alhawarin et al. (2021); Culbertson et al. (2016); Rozo and Sviatschi (2021); Tiltnes et al. (2019) on housing and overcrowding in urban areas; Kamyab (2017); Panter-Brick et al. (2018) on children and education; (Dator et al., 2018) on healthcare; (Mabiso et al., 2022) on food security; Ajluni and Kawar (2021); Fallah et al. (2019) on the labor market; and (Breulmann et al., 2021) on water supply.

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comparatively less attention has been devoted to understanding how refugee households themselves sustain well-being and adapt to persistent stressors. The protracted nature of displacement in Jordan has meant that refugee welfare increasingly depends on humanitarian assistance, particularly cash-based transfers that provide households with flexibility to meet essential needs. Jordan now ranks among UNHCR's largest global cash-assistance operations. For example, in 2016 UNHCR's cash-assistance programs reached over 136,000 Syrian refugees, disbursing USD 85 million, and by 2022 they reached roughly 300,000 refugees, with total transfers of about USD 180 million (Giordano et al., 2017). A key empirical and policy question, therefore, concerns the extent to which such assistance contributes to refugee households' resilience. Tackling the multifaceted challenges posed by the refugee crisis in Jordan (Berti, 2015) requires comprehensive strategies that promote social inclusion while ensuring the provision of essential services for vulnerable populations—both refugees and host communities—amid ongoing structural challenges such as water scarcity and recent shocks, including the COVID-19 pandemic (Hussein et al., 2020).

Against this background, this paper examines how refugee households' dependence on cash assistance relates to their estimated economic resilience. Designing and evaluating such support strategies effectively require quantitative measures of refugee livelihood conditions, based on extensive and timely data collection. In this respect, UNHCR's quarterly assessment, launched in 2022 as part of its ongoing Vulnerability Assessment Framework (VAF), provides a unique opportunity to monitor the evolving conditions of refugee households in Jordan. Using these data, we develop a probabilistic, outcome-based measure of household resilience and employ panel regressions to assess whether dependence on cash assistance is associated with a higher capacity to sustain a minimum normative standard of well-being under potential stressors.

Following the seminal contribution by Cissé and Barrett (2018), we frame the concept of household resilience in terms of the "ability to achieve and maintain an acceptable standard of well-being even in the face of shocks and stressors" (Barrett & Constas, 2014). Therefore, in line with the "resilience as an ability" framework, household resilience is defined here as the probability of attaining and preserving a normatively anchored acceptable level of well-being, conditional on past household livelihood, and demographic/geographic controls (Upton et al., 2022).

The paper aims to make three original contributions. First, our work extends to the population of refugees the economic literature on resilience, which so far has mostly focused on rural contexts, with particular emphasis on resilience to food security (Ansah et al., 2019). Notwithstanding some recent contributions have begun to tackle the issue of quantitatively estimating household resilience among displaced populations,[2] scholarly work that empirically characterizes resilience of forcibly displaced households and its underlying dynamics is currently scant (Maria Pinto et al., 2014). Second, we use two interdependent measures of refugee household well-being—real per-capita income and the survival minimum expenditure basket—and estimate resilience as the joint conditional probability that both indicators exceed their respective minimally acceptable, normative thresholds, accounting for their covariance. This approach extends the Cissé–Barrett framework and refines the methodology of Vaitla et al. (2020), who estimate overall resilience using marginal conditional probabilities that treat the indicators as statistically independent. Our results show that incorporating the correlation between the two indicators substantially improves the precision of predicted shares of resilient households across a range of probability thresholds. Third, we examine the statistical association between refugee household dependence on cash assistance and their estimated resilience. Beyond its clear policy relevance—given the scale of UNHCR and WFP's cash transfer programs in Jordan—this question contributes to a growing literature on cash transfers and social protection, which underscores their potential to strengthen household resilience and well-being, particularly in contexts of vulnerability and forced displacement (see Abu Hamad et al., 2025, for the case of Jordan).

In sum, our analysis indicates that refugee households in Jordan residing in higher-income or less densely populated Governorates tend to exhibit higher resilience levels than those living elsewhere. However, across the four quarters of 2022, refugee households experienced a decline in their ability to maintain a minimum standard of well-being, with those living outside Amman and of Syrian nationality showing lower levels of resilience. We also find evidence of a positive contemporaneous association between cash assistance and household resilience, with the largest impacts observed among the most vulnerable households. Although not identified through exogenous variation, this association—consistently emerging across alternative econometric specifications—can be cautiously interpreted as suggestive of a causal relationship, under reasonable assumptions and with due caveats.

The rest of the paper is organized as follows. Section 2 provides a discussion of the Jordanian context and the refugee crisis, while Section 3 offers a brief review of the literature focusing on estimating household resilience. Section 4 introduces the dataset and the variables employed in the analysis, whose details are described in Section 5. Our main results are presented in Section 6 and discussed in Section 7, which also contains some final remarks.

2. Background on Jordan and the refugee crisis

The country of Jordan has long served as a refuge for displaced populations from neighboring regions. Since its founding, it has hosted successive refugee inflows (e.g., Palestinians after 1948 and 1967, Iraqis after 1990 and 2003, and most recently Syrians since 2011). These repeated inflows have profoundly shaped the country's demographic composition and development trajectory, imposing pressure on already limited natural and institutional resources. After the outbreak of the Syrian civil war, Jordan has become one of the world's largest refugee-hosting countries relative to population size. By 2023, estimates suggest between 700,000 and 1.3 million registered refugees, equivalent to 7–11% of Jordan's total population, with Syrians constituting the majority (Alrababa'h et al., 2021). The influx has been accompanied by a sharp increase in demand for housing, water, energy, and public services, while employment opportunities have remained scarce, particularly for low-skilled refugees. These strains have amplified long-standing vulnerabilities in Jordan's economy, including high unemployment, dependence on imports, and water scarcity (Alshoubaki & Harris, 2018; Carrion, 2015; Muller et al., 2016).

While Jordan's public infrastructure and governance capacity have remained relatively stable compared to many countries in the region, the sudden and persistent growth in population has generated fiscal and social pressures. The refugee crisis has required extensive external assistance to sustain basic services, leading to recurrent appeals for international burden-sharing. In the attempt to facilitate refugees' inclusion in Jordan, a number of plans have been developed including the "Jordan Compact"—negotiated between the European Commission, the World Bank, and the Government of Jordan—aimed at including refugees in the domestic labor market (Gordon, 2021; Lenner & Turner, 2019) and the "Regional Refugee and Resilience Plan" (3RP)—an integrated humanitarian and resilience response to the situation facing refugees and host communities with clear strategic directions guiding the coordination of responses at both regional and country levels. The spatial concentration of refugees in urban areas (especially Amman, Irbid, and Mafraq) has further intensified competition for affordable housing and local jobs. Refugee households typically face higher rent burdens, while host communities experience price increases and labor market competition. However, studies find that the macroeconomic impacts of the Syrian crisis on Jordan have been mixed, with limited aggregate effects on wages or employment but significant distributional consequences across skill levels and locations (e.g. Ajluni & Kawar, 2021; Fallah et al., 2019).

[2] Cf. FAO (2018) for Jordan, Fisseha et al. (2025) for Ethiopia and Marciano et al. (2025) for Israel, among a few others.

Access to water, sanitation, and health care remains particularly strained. Jordan ranks among the most water-scarce countries worldwide, and refugee settlements—both camps and urban clusters—have exacerbated demand on aquifers and wastewater infrastructure (Breulmann et al., 2021). Despite major investments in emergency water trucking and wastewater management, the balance between humanitarian supply and environmental sustainability remains fragile. The refugee influx has also interacted with pre-existing socioeconomic inequalities. While host communities have benefited from local aid and infrastructure projects, the uneven distribution of assistance across Governorates has created perceptions of unfairness and competition for limited resources. These tensions have been further compounded by the COVID-19 pandemic, which disrupted labor markets and service provision, disproportionately affecting informal workers and refugees (Kattaa et al., 2022). Jordan's institutional response to the refugee crisis has been notable for its coordination between humanitarian and national actors. The Jordan Response Plan (JRP), first launched in 2015, integrates humanitarian relief with longer-term resilience and development goals, linking international funding with national planning frameworks. Through the JRP and subsequent iterations, Jordan has become a reference model for "resilience-based response approaches", emphasizing host–refugee inclusion, predictable financing, and local ownership (Berti, 2015; Hussein et al., 2020).

Within this framework, cash-based assistance has emerged as a central pillar of the humanitarian response for Syrian refugees. Managed primarily by UNHCR and the World Food Programme (WFP), these programs channel multi-purpose cash and food vouchers to hundreds of thousands of vulnerable households each year. In 2022, UNHCR provided cash support to around 300,000 refugees, with total disbursements exceeding USD 180 million (UNHCR, 2023c). The assistance system relies on sophisticated targeting instruments such as the Vulnerability Assessment Framework (VAF, UNHCR, 2019), which continuously ranks refugee households by vulnerability and integrates socioeconomic indicators from multiple partners. Cash assistance plays a dual role: it alleviates short-term consumption constraints and indirectly supports local demand, while its design also aims to foster self-reliance and reduce negative coping strategies such as debt accumulation or asset depletion (Abu Hamad et al., 2015). Evidence from Jordan and other displacement settings shows that well-targeted cash transfers can stabilize welfare, improve food security, and facilitate access to education and healthcare (Gassmann et al., 2023; Premand & Stoeffler, 2022).

Despite these achievements, humanitarian funding remains volatile, and coverage is partial. Many households cycle in and out of eligibility depending on changing needs assessments, creating uncertainty and vulnerability. Understanding how such assistance interacts with refugee household resilience is therefore critical, particularly in a protracted context where economic self-reliance and humanitarian support must coexist. This paper contributes to this discussion by quantitatively assessing the link between cash assistance and resilience using quarterly microdata from UNHCR's 2022 monitoring system.

3. Estimating household resilience: a brief overview

The notion of *resilience* has gained prominence across economics, development, and humanitarian studies as a framework for understanding how households sustain well-being under stress. Yet, despite broad adoption, definitions and measurement strategies vary considerably across disciplines. Early frameworks conceptualized resilience as a process of recovery or adaptation to shocks, often rooted in ecology or systems theory (Adger, 2000). More recent economic approaches, however, have emphasized a normative and probabilistic interpretation—*resilience as the capacity to maintain an acceptable level of well-being in the face of shocks* (Barrett & Constas, 2014). This shift allows resilience to be empirically linked to welfare indicators and estimated using standard econometric tools.

The framework proposed by Cissé and Barrett (2018) formalizes this perspective by defining resilience as a conditional probability derived from observed data on livelihoods and shocks.[3] Specifically, household resilience is modeled as the probability that welfare, $W_{h,t}$, remains above a normative threshold W^*, conditional on past welfare, shocks, and controls. This outcome-based and predictive approach has been widely adopted in recent empirical work (Upton et al., 2022). The Cissé–Barrett (CB) framework combines two elements: (i) a stochastic model of livelihood dynamics that captures persistence in welfare outcomes, and (ii) a normative welfare threshold that operationalizes the notion of "acceptable well-being." The resilience measure, denoted $\hat{\rho}_{h,t}$, represents the estimated probability that a household's expected welfare exceeds the threshold, given its past trajectory and covariates. This allows resilience to be interpreted as a forward-looking indicator, bridging the gap between vulnerability analysis and welfare dynamics.

This probabilistic, outcome-based formulation is particularly suited for contexts where information on actual shocks or recovery paths is limited. In such cases, resilience can be inferred from observed livelihood trajectories, under the assumption that past outcomes encapsulate both exposure to and recovery from unobserved stressors. The resulting measure captures the likelihood that a household sustains a minimum well-being level under potential adversity, rather than its ability to transform or adapt in response to specific shocks. As such, it aligns with the concept of "resilience as stability" (Barrett & Constas, 2014), focusing on sustained welfare rather than transformation. The CB approach thus differs from earlier indices (e.g., RIMA-II, cf. FAO, 2016), which construct resilience scores from multiple ex-post indicators. Instead, it directly estimates resilience probabilities from welfare dynamics, yielding a metric with explicit statistical interpretation and uncertainty bounds. In addition, it accommodates both cross-sectional and longitudinal data and allows for extensions such as joint probabilities across multiple welfare indicators.

In this paper, we build on this probabilistic perspective and estimate the joint conditional probability that two key welfare indicators—-real per capita income and expenditure relative to the Survival Minimum Expenditure Basket (SMEB)—-remain above their respective normative thresholds. This formulation allows resilience to be interpreted as the ability of households to maintain both adequate income and expenditure simultaneously, taking into account their interdependence. Overall, the CB-based framework offers a coherent and statistically tractable way to operationalize the concept of resilience, linking it directly to observable welfare outcomes and enabling quantitative policy analysis in displacement settings.

4. Data and variables

We leverage UNHCR data from the "Quarterly Assessment of the Socio-Economic Situation of Refugees". The survey monitors refugee vulnerability in Jordan in year 2022[4] (UNHCR, 2023b), using the VAF as a baseline and collecting information from the same refugee households on a quarterly basis over a wide array of dimensions, including economic vulnerability and livelihoods; food security; shelter; access to water, sanitation and hygiene (WASH); and health. Refugee households in the database live in hosting communities and their geographical

[3] Cf. the reviews in Barrett et al. (2021) and Upton et al. (2022), related applications (Abay et al., 2022; Lee et al., 2023; Premand & Stoeffler, 2022) and methodological extensions (Scognamillo et al., 2023; Vaitla et al., 2020).

[4] See https://microdata.unhcr.org/index.php/catalog/847. The 2023 wave of the assessment is now available but, to our knowledge, does not follow the same households surveyed in 2022. Hence, it cannot be merged with the current panel without losing longitudinal consistency. Future research could use the 2023 data to extend the analysis through pooled or comparative yearly panels.

Fig. 1. Map of the 12 governorates in the hashemite kingdom of Jordan.

location is identified according to GADM-1 level (i.e., the 12 Jordan Governorates, see Fig. 1).[5]

The original database features a total of 14,208 household observations in the whole 2022 year, for which we have information spanning 295 variables. After a preliminary cleaning, aimed at minimizing missing-value issues and removing variables that do not exhibit sufficient variation across households and waves, we end up with a balanced dataset consisting of 10,524 observations, i.e., 2631 refugee households repeatedly surveyed across the four waves (quarters in year 2022).[6]

In our sample, the shares of refugee households are stable across the four waves in each Governorate (see Table A1 in Appendix A). About half of refugee households are located in the Amman Governorate, while the majority of the other half are concentrated in Irbid (15.2%) and Mafraq (11.5%). Fig. 2 shows that household sample sizes across Governorates are positively correlated with both Governorate total population and population density in year 2022.

Out of the original 295 variables associated with each refugee household, we have distilled a set of relevant information regarding our main dimensions of interest: household livelihood, shelter vulnerability (i.e., existence of any threats of eviction), and dependence on (unconditional) assistance.

Our main livelihood indicators are household "SMEB" (Survival Minimum Expenditure Basket) and "INCOME". The "SMEB" variable is

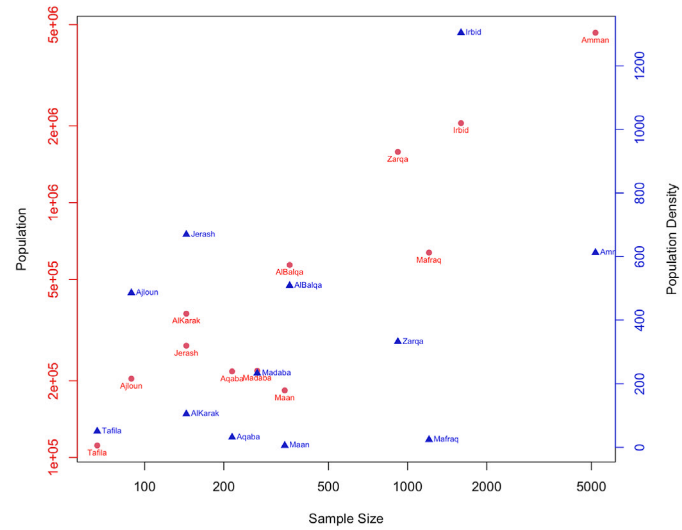

Fig. 2. Number of refugee households in the pooled sample across governorates vs governorate total population and population density in year 2022.

defined as real per-capita monthly survival minimum expenditure basket and is built out of original nominal expenditure levels for food, rent, electricity, water, basic items and hygiene using UNHCR definitions.[7] Per-capita figures are computed using household size and deflated employing item-specific Jordan price indices for year 2022. Per-capita real income ("INCOME") is computed using the same procedure and deflated by the Consumer Price Index (CPI), available for the Jordan aggregate across the four quarters of year 2022.[8]

As far as assistance is concerned, we build two variables that measure the extent to which household total income is dependent on (unconditional) cash assistance. The first one ("Dep Assistance Ratio") measures the share of total household income coming from assistance sources. These include unconditional cash assistance from UNHCR and WFP initiatives, in which the household is enrolled. The second one ("Dep Assistance Binary") is a dummy variable taking value equal to one if the household displays a "Dep Assistance Ratio" that is above the pooled average (= 0.568), and zero otherwise. Furthermore, we employ a dummy variable indicating if cash from assistance has been employed to pay the rent ("Rent Assistance"). To further refine our exercises, we also use two dummy variables that tell us whether a household is enrolled in (vs. phased out) WFP cash initiatives and whether it is currently eligible to receive cash assistance from either WFP or UNHCR.

Note that in constructing the income indicator used to estimate household resilience, we excluded income from assistance so that the measure reflects households' self-generated economic capacity. By contrast, when defining the dependence-on-assistance variables, we followed UNHCR's convention and measured the share of total income accounted for by assistance, dividing assistance receipts by total household income (including assistance). This ensures that the ratio is bounded between zero and one and correctly captures the intensity of dependence.

We finally create a set of household socio-demographic characteristics, which are employed as controls in our resilience regression

[5] The survey employs random sampling of UNHCR-registered refugees across Jordan, with sample sizes drawn from the proGres registration database. Household geo-referencing is coarse, and the dataset lacks key details on urban/rural location, hosting-community features, gender, assets, and employment. Since Q3 2022, coverage has expanded to refugees in the Azraq and Zaatari camps, but due to limited time coverage, camp households are excluded from this analysis.

[6] Variables with extensive missingness were excluded to preserve a balanced panel and maintain statistical power, following standard practice in conditional-moment applications (cf., e.g., Lee et al., 2023). Because missingness may be non-random, we acknowledge this potential bias. Future work could apply multiple imputation or alternative covariate sets to test robustness.

[7] See data2.unhcr.org/fr/documents/details/86576.

[8] Price indices and CPI are retrieved from the Jordan Department of Statistics (DoS; dosweb.dos.gov.jo/economic/price-indices/table-price-indices). All nominal income and SMEB values are deflated using national indices to express them in constant 2022 prices. Regional price indices are unavailable, preventing adjustment for local cost variations—e.g., those related to refugee concentration or market conditions. Consequently, real values may slightly understate (overstate) welfare where prices rose faster (slower) than the national average.

specifications (see Table A2 in Appendix A for more details on the full set of variables employed in the analysis). These include four dummies respectively equals to 1 if the household is Syrian ("Syrian"); if the household head is married ("Head Married"), has attended secondary school ("Head Educated") and if is older than 50 ("Head Old"). Note that age is recorded in the dataset in four categorical bands: 18–24, 25–49, 50–59, and over 60 years. This follows UNHCR's standard classification for their "Quarterly Assessment" surveys. Consequently, the 50-year threshold derives directly from the survey design rather than from an arbitrary choice. In our sample, 31.8% of household heads fall into the 50+ categories, while 68.2% are younger. Although this cutoff is slightly above the sample median age, it meaningfully separates households that may face different labor market constraints, health challenges, and adaptive capacities in the refugee context. In addition, to control for household disability, we employ a disability dummy variable ("Head Disability") equal to one if the sum over six related dimensions (seeing, hearing, walking, remembering, self-care, and communication) exceeds 12, i.e., the average value computed over the six dimensions, taken values on a 1–4 scale (1 = Good, 4 = Worse), see WGDS (2021) for details. We also have a measure of household size ("HH Size") as well as a binary "Eviction Threat" indicator, which in our analysis plays the role of an idiosyncratic stressor, that tracks households that are currently under a threat of eviction (cf. Section 7 for a discussion).

Our descriptive statistics, reported in Tables 1 and 2, show that a large majority of refugee households are Syrian, with a head who is married, young and poorly educated, but without disability conditions. Most refugee households are not currently under a threat of eviction, half of the population is dependent on assistance and about 40% paid rent through assistance. As far as the evolution over time of the variables of interest is concerned, the percentage of observations equal to one for binary variables (Table 2) remains fairly stable across the four waves, while both the mean and median of SMEB and INCOME tend to slightly decline over the year. Note also that 63% of refugee households remain enrolled in WFP assistance program for all four waves, while the remaining 37% do not. Further computations indicate that about 27% of refugee households continue to be dependent on assistance ("Dep Assistance Binary" = 1) across three of four consecutive waves, whereas about one third never exhibit dependence. Moreover, the variable "Dep Assistance Ratio" exhibits an autocorrelation coefficient of 0.714. This indicates that household dependence on assistance remains strongly persistent in our sample.

Table 1
Descriptive statistics. Ratio, discrete, and continuous variables by waves and in pooled sample.

Wave	Variable	Mean	Median	Min	Max	Std Dev	Skewness	Kurtosis
1	Size	4.90	5.00	1.00	20.00	2.48	0.63	3.98
	Dep Assistance Ratio	0.60	0.65	0.00	1.00	0.39	−0.32	1.55
	SMEB	48.21	36.72	0.00	574.79	45.89	3.60	25.69
	INCOME	57.36	47.50	0.00	900.00	55.14	4.89	48.08
2	Size	4.98	5.00	1.00	20.00	2.46	0.65	4.16
	Dep Assistance Ratio	0.59	0.61	0.00	1.00	0.39	−0.25	1.52
	SMEB	43.83	34.03	0.00	479.36	40.57	2.96	18.69
	INCOME	56.49	47.44	0.00	988.43	51.57	5.12	59.53
3	Size	5.08	5.00	1.00	20.00	2.49	0.68	4.35
	Dep Assistance Ratio	0.55	0.53	0.00	1.00	0.40	−0.10	1.37
	SMEB	41.38	33.34	0.00	500.79	37.84	3.53	28.26
	INCOME	52.17	41.44	0.00	726.36	50.18	4.61	41.30
4	Size	5.05	5.00	1.00	17.00	2.44	0.51	3.44
	Dep Assistance Ratio	0.53	0.53	0.00	1.00	0.36	−0.06	1.66
	SMEB	40.84	32.36	0.00	518.05	39.10	3.23	21.98
	INCOME	51.63	41.18	0.00	770.15	50.02	3.35	28.94
Pooled	Size	5.00	5.00	1.00	20.00	2.47	0.62	3.99
	Dep Assistance Ratio	0.57	0.58	0.00	1.00	0.38	−0.18	1.50
	SMEB	43.81	33.99	0.00	574.79	41.05	3.39	24.37
	INCOME	56.91	47.12	0.00	988.43	51.87	4.52	45.10

Table 2
Descriptive statistics. Binary variables. Percentage of observations with variable equal to one by waves and in pooled sample.

Variable Name	Waves				
	1	2	3	4	Pooled
Head Old	0.29	0.29	0.30	0.28	0.29
Head Married	0.73	0.76	0.75	0.75	0.75
Head Educated	0.31	0.32	0.30	0.31	0.31
Head Disability	0.21	0.24	0.26	0.26	0.24
Amman Govt	0.48	0.50	0.49	0.49	0.49
Syrian	0.62	0.62	0.62	0.62	0.62
Cash Eligibility	0.34	0.34	0.34	0.34	0.34
WFP	0.63	0.63	0.63	0.63	0.63
Eviction Threats	0.27	0.29	0.26	0.27	0.27
Dep Assistance Binary	0.56	0.54	0.50	0.49	0.52
Rent Assistance	0.44	0.40	0.39	0.44	0.42

5. Methods

5.1. *The Cissé-Barrett approach*

Our main objective is to use the CB approach to infer a quantitative measure of refugee household resilience that controls for household characteristics and is anchored to some exogenously recognized normative minimum livelihood standards. In a nutshell, the strategy consists of the following steps. First, a household livelihood indicator $y_{h,t}$, for which we can identify some commonly accepted exogenous minimum livelihood-standard threshold y^*, is regressed against a degree-d polynomial of lagged values thereof:

$$P^d(y_{h,t-1}) = \beta_0 + \beta_1 y_{h,t-1} + \beta_2 y_{h,t-1}^2 + \cdots + \beta_{d-1} y_{h,t-1}^{d-1} + \beta_d y_{h,t-1}^d, \tag{1}$$

household controls and shocks $X_{h,t}$, and a set of dummy variables $D_{k(h)}$, where h stands for household, $k(h)$ is some possible aggregation of households by groups, and t for time (i.e., waves in our survey data; cf. Section 5.2 for a more formal description of the implementation of the CB strategy to our case study). According to the nature of the dependent variable, the regression can be fitted using OLS, Poisson or other estimators. Predicted values $\hat{y}_{h,t}$ of that regression are taken as an estimate of the conditional first moment of $y_{h,t}$.

Second, squared residuals $e_{h,t}^2$ from the first fit are regressed again on $P^d(y_{h,t-1})$, $X_{h,t}$, and $D_{k(h)}$. This allows one to obtain an estimate $\hat{e}_{h,t}^2$ of the conditional second moment of $y_{h,t}$. Note that both conditional first and second moments are household and wave specific, and are defined for all waves $t \geq 2$.

Third, one assumes that, conditionally on the covariates, the household livelihood indicator $y_{h,t}$ is distributed as a random variable that is fully characterized by its first two moments only, i.e., by two parameters $(\theta_{h,t}, \vartheta_{h,t})$. Some natural options in the case $y_{h,t} \geq 0$ are log-normally or Gamma distributed random variables.

Fourth, $(\hat{y}_{h,t}, \hat{e}_{h,t}^2)$ are employed to obtain an estimate for the two parameters $(\theta_{h,t}, \vartheta_{h,t})$ characterizing the cumulative distribution function (CDF) of the assumed random variable for $y_{h,t}$:

$$\text{prob}\{y_{h,t} \leq y | P^d(y_{h,t-1}), X_{h,t}, D_{k(h)}\} = F_{h,t}(y | P^d(y_{h,t-1}), X_{h,t}, D_{k(h)}; \hat{\theta}_{h,t}, \hat{\vartheta}_{h,t}). \tag{2}$$

Again, the resulting CDFs are both household and wave specific.

Finally, given the identified normative minimum livelihood standard threshold y^*, household resilience is defined as:

$$\hat{\rho}_{h,t} = 1 - F_{h,t}(y^* | P^d(y_{h,t-1}), X_{h,t}, D_{k(h)}; \hat{\theta}_{h,t}, \hat{\vartheta}_{h,t}), \tag{3}$$

that is as the conditional probability that a household h is able to achieve in wave t a minimum level of well-being. One can then set some exogenous probability threshold (e.g., $\rho^* = 0.5$) to define household h to be resilient in wave t iff $\hat{\rho}_{h,t} > \rho^*$. It is important to note that, in our empirical setting, the estimated probability of remaining above welfare thresholds reflects a form of economic resilience, i.e., the ability to sustain a basic living standard under potential stressors. In the absence of data on realized shocks or recovery trajectories, this measure should be interpreted as a predictive stability metric—consistent with the "ability to maintain well-being" approach proposed by CB, rather than a comprehensive measure of adaptive or transformative resilience.

5.2. Refugee households in Jordan: implementation of the CB approach

To implement the CB approach in the case of Jordanian refugee households, we begin by choosing the livelihood (dependent) variables. In line with Vaitla et al. (2020), who compare household resilience using two different well-being indicators, we employ both the SMEB and the INCOME variables separately, i.e. $y_{h,t} \in \{\text{SMEB}_{h,t}, \text{INCOME}_{h,t}\}$.

For either variable, we identify a minimum livelihood standard threshold. In the case of SMEB, we employ the estimated monthly minimum expenditure basket (MEB) for Syrian refugees in Jordan (in year 2022) as computed in UNHCR (2022a). After re-scaling that figure by household size and deflating it by the CPI, we obtain an estimate for the real per-capita SMEB minimum threshold $y^*(\text{SMEB}) = 66.68$ JOR. As for INCOME, we rely on the international poverty line of 2.15 USD (2017 PPP) per day, which (using the Jordan GDP deflator) gives us an estimate of our real per-capita monthly INCOME minimum threshold $y^*(\text{INCOME}) = 69.52$ JOR (cf. also UNHCR, 2019).

Since both SMEB and INCOME are right-skewed (with means larger than medians, cf. Table 1), it is safer to enter the dependent variables as logs in the first-moment specification. Covariates always include a degree-d polynomial $P^d(y_{h,t-1})$ of lagged dependent variable. An extensive battery of preliminary tests suggests that the best choice for d is 4 in the case of SMEB and 2 in the case of INCOME, as additional powers become statistically insignificant. Furthermore, we employ a set of controls $X_{h,t}$ featuring demographic variables as described in Section 4. All specifications also include Governorate dummies and standard errors are clustered at the Governorate level.[9] Therefore, fully in line with the CB approach (cf. Section 5.1), our first-moment specification reads:

$$\log(y_{h,t}) = P^d(y_{h,t-1}) + \alpha X_{h,t} + \gamma D_G + \epsilon_{h,t}, \tag{4}$$

where $y_{h,t} \in \{\text{SMEB}_{h,t}; \text{INCOME}_{h,t}\}$; D_G are Governorate dummies; $X_{h,t}$ is a vector of household demographic controls and stressor variables ("Head Old", "Head Married", "Head Educated", "Head Disability", "Syrian", household "Size", and "Eviction Threat"); and $\epsilon_{h,t}$ is the error. We estimate Eq. (4) using OLS and check the robustness of our results when the dependent variable enters in levels and either a generalized-linear model (GLM) regression with log link or a Poisson estimator is employed. As to the second-moment equation, squared residuals $\hat{\epsilon}^2_{h,t}$ from Eq. (4) are regressed against the same battery of covariates of the first-moment estimation using a Poisson estimator, as done in Cissé and Barrett (2018). Two points merit emphasis. First, household fixed effects are excluded from both first and second moment estimations because they would absorb the very household-specific, time-invariant heterogeneity that the conditional moments approach seeks to measure. By removing this cross-household variation, fixed effects would limit the analysis to within-household changes, undermining the model's ability to capture and compare differences in predictive resilience across households—the core purpose of the CB framework, which we rely upon in this study. Second, still in line with that framework, idiosyncratic shocks (here, "eviction threat") are included in the conditioning set $X_{h,t}$ for both the mean and variance equations. Shocks thus shift the conditional distribution of INCOME/SMEB and, by construction, resilience probabilities relative to fixed normative thresholds, but they are not components of those thresholds.

Predicted values from the two regressions above allow us to obtain estimates $(\hat{m}_{h,t}, \hat{v}_{h,t})$ of the conditional first and second moments of $\log(y_{h,t})$ for both household SMEB and INCOME across the waves. We begin by assuming that $y_{h,t}$ is conditionally distributed as a log-normal and we subsequently check if results are robust to assuming that the conditional distribution of $y_{h,t}$ is Gamma instead. In the first case, to retrieve estimates of log-normal parameters, one can directly compute resilience probabilities in Eq. (3) using the fact that $\log(y_{h,t})$ is conditionally distributed as a Gaussian with parameters $(\hat{m}_{h,t}, \hat{v}_{h,t})$ and normalizing the threshold y^* accordingly. In the case where one assumes that $y_{h,t}$ is conditionally distributed as a Gamma$(\theta_{h,t}, \vartheta_{h,t})$—and therefore that $\log(y_{h,t})$ is log-gamma distributed—two alternative equivalent procedures can be implemented. First, following Halliwell (2021), we can retrieve $\hat{\theta}_{h,t}$ by numerically solving the non-linear equation $\hat{v}_{h,t} = \Psi'(\theta_{h,t})$, where Ψ' is the trigamma function. An estimate for $\vartheta_{h,t}$ can then be computed by setting $\hat{\vartheta}_{h,t} = \exp\{\hat{m}_{h,t} - \Psi(\hat{\theta}_{h,t})\}$, where Ψ is the digamma function. Second, Eq. (4) can be estimated in levels rather than in logs (e.g., with a Poisson estimator) to obtain the conditional mean $\hat{\mu}_{h,t}$ of $y_{h,t}$. Subsequently, $\hat{\mu}_{h,t}$ and the estimate for the conditional second moment $\hat{\varsigma}_{h,t}$ can be used to infer $(\theta_{h,t}, \vartheta_{h,t})$ by setting $\hat{\theta}_{h,t} = \hat{\mu}^2_{h,t}/\hat{\varsigma}_{h,t}$ and $\hat{\vartheta}_{h,t} = \hat{\varsigma}_{h,t}/\hat{\mu}_{h,t}$. Eventually, we end up with two estimates of refugee household resilience probabilities $\{\hat{\rho}_{h,t}, t = 2, 3, 4\}$, the first one for SMEB and the second for INCOME, either in the case where we assume that our livelihood indicator is conditionally distributed as a log-normal or as a Gamma.

Given a chosen livelihood indicator, a household is deemed resilient if its estimated resilience probability exceeds a threshold ρ^*. When multiple indicators are used, overall household resilience can be assessed by checking whether the estimated probabilities $\hat{\rho}_{h,t}$ exceed ρ^* in both SMEB and INCOME dimensions. Since livelihood indicators are typically positively correlated–as confirmed by the pooled Pearson correlation of 0.5463 between SMEB and INCOME in our data–the corresponding resilience probabilities $\hat{\rho}_{h,t}$ are also likely to be correlated. Evaluating overall resilience from marginal probabilities alone, as if SMEB and INCOME were independent, would therefore yield biased estimates.

To address this, we extend the CB approach by estimating the joint conditional probability that both SMEB and INCOME exceed their normative thresholds, assuming a bivariate log-normal distribution. The joint distribution depends on five parameters, four estimated previously. The remaining parameter (i.e., the conditional correlation coefficient) is obtained by regressing the product of residuals from the SMEB and INCOME first-moment equations on the same set of controls and lagged variables. This provides the conditional correlation coefficient, allowing full characterization of the joint probability that households meet both well-being thresholds.

5.3. Link between resilience probabilities and household dependence on assistance

Once an indicator of household resilience has been determined, we aim to understand how this is associated with household dependence on assistance. While the policy relevance of assessing the impact of cash assistance on household resilience is well established and widely discussed in the literature (see Section 3), addressing this question empirically poses significant methodological challenges due to the endogeneity inherent in the targeting of cash assistance.

As discussed above, in Jordan, as in many other refugee-hosting contexts, cash-based interventions are allocated according to targeting policies, whereby the most vulnerable households are prioritized for assistance. Since treatment is not random, this design creates a potential reverse causality problem: while dependence on assistance may shape household resilience trajectories, resilience itself (or the lack thereof)

[9] Following Cissé and Barrett (2018), we do not include time dummies, as this would remove changes in conditional distributions across waves, which is a source of variation we want to retain in our analysis.

may be correlated with the very criteria determining eligibility for transfers. Such dynamics complicate causal inference, as resilience (or its correlates) predicts cash assistance and observed associations may reflect targeting rules rather than the independent impact of assistance. This concern echoes broader debates in the social protection and development economics literature, where endogeneity between program participation and outcomes has been highlighted as a key methodological hurdle in evaluating poverty alleviation and resilience-building interventions (Angelucci, 2008; Baird et al., 2018; Deaton, 2010).

Since our dataset lacks exogenous variation in assistance provision (e.g., from policy reforms or administrative cut-offs), we cannot credibly implement quasi-experimental designs such as regression discontinuity or difference-in-differences. Instead, we rely on a set of household fixed-effects panel regressions, complemented by robustness checks and quantile regressions, to examine whether dependence on assistance is positively (and contemporaneously) associated with resilience, and to interpret results in light of potential targeting bias. In this way, we make a preliminary and cautious attempt at partially disentangling the causal effect of unconditional cash assistance from the underlying vulnerabilities that shape both program participation and resilience outcomes.

More specifically, our baseline panel-regression specification reads:

$$\hat{\rho}_{h,t} = \kappa_h + \omega A_{h,t} + \xi X_{h,t} + \nu D_t + \upsilon_{h,t}, \tag{5}$$

where t indexes survey waves; κ_h are household-level fixed effects (FEs); $X_{h,t}$ is a vector of household demographic controls and stressor variables that, in addition to those already employed to estimate resilience, also includes "Cash Eligibility" and "WFP" dummies (more on this in Section 6.4); D_t are wave dummies absorbing common level differences across time periods; and $\upsilon_{h,t}$ is the error term. The covariate of interest ($A_{h,t}$) is household dependence on assistance, which we measure using the three main indicators discussed in Section 4, i.e., the two dummy variables "Dep Assistance Binary" and "Rent Assistance", as well as the continuous variable "Dep Assistance Ratio", which we employ both linearly ("linear") and as a quadratic polynomial ("squared"). We use throughout a FE estimator with standard errors clustered at the household level.[10] Here, household FEs absorb unobserved time-invariant heterogeneity that might jointly influence A and $\hat{\rho}$, thereby mitigating an important potential source of bias. Therefore, identification of ω relies on within-household variation in assistance over time, though residual endogeneity may remain.

Indeed, as cash assistance is targeted to vulnerable households (that likely exhibit low resilience at baseline), past resilience $\hat{\rho}_{h,t-1}$ may negatively predict today's dependence on assistance ($A_{i,t}$). In this case, since resilience is strongly persistent,[11] current resilience still predicts current assistance and therefore $\hat{\omega}$ may be biased). This echoes the classic policy endogeneity issue, where aid agencies or governments allocate today's transfers based on prior hardship. To partially control for persistence, we therefore run a second regression specification where we add among regressors a lagged resilience term:

$$\hat{\rho}_{h,t} = \phi\hat{\rho}_{h,t-1} + \kappa_h + \omega A_{h,t} + \xi X_{h,t} + \nu D_t + \upsilon_{h,t}, \tag{6}$$

This absorbs persistence in resilience, though with few time periods it may introduce small-sample Nickell bias (Nickell, 1981). Note that while our specification includes a lagged dependent variable under fixed effects, the short time dimension of our panel (three effective waves) makes dynamic-panel estimators such as difference or system GMM impractical, given the limited depth for valid instruments and the risk of instrument proliferation (Judson & Owen, 1999). In this context, the fixed-effects estimator remains a consistent choice for large N and small T panels, although the coefficient on the lagged dependent variable may be, as mentioned, biased downward. As such, our estimated persistence coefficient should be interpreted as a lower bound on true resilience persistence. Importantly, this bias primarily affects the lag term and does not distort the estimated contemporaneous relationship between assistance and resilience, which remains the focus of our empirical analysis.

We further check the robustness of our results by adding in both Eq. (5) and (6) household-specific linear time trends ($\nu_h \cdot t$). This is because, after having washed away time-invariant heterogeneity and persistence of the dependent variable, there may still be time-varying unobservables that are correlated with both assistance and resilience. These slow-moving, household-specific evolutions might be associated with factors determining policy targeting, different from those we accounted for in the controls used (e.g., household size and head disability), thus biasing our estimates. Next, we test for any anticipatory effects by adding to the right-hand side a lead of the assistance variable ($A_{h,t+1}$). Indeed, if assistance were systematically anticipated (e.g., households knowing in advance and adjusting resilience-related behavior), one would expect significant leads. We do so by inserting into the right-hand side of both Eq. (5) and (6) the lead either alone or together with the contemporaneous assistance variable ($A_{h,t}$). Finally, we complement FE regressions in Eqs. (5) and (6) with quantile regressions of $\hat{\rho}_{h,t}$ on $A_{h,t}$, to examine heterogeneity of the contemporaneous-assistance impact across the distribution of resilience, when the assistance variable employed is the dummy "Dep Assistance Binary". Given that targeting rules are strongest at the bottom of the resilience distribution, this exercise may help disentangle whether observed effects follow a theoretical pattern (i.e., larger impacts among the most vulnerable) or a selection-driven profile (e.g., spurious and inconsistent structure).

It is worth noting that the dependent variable $\hat{\rho}_{h,t}$ in Eqs. (5) and (6), is a generated measure obtained from the CB procedure. Following standard practice in the resilience literature, we treat $\hat{\rho}_{h,t}$ as a consistent proxy for household resilience and use conventional panel estimators with clustered standard errors. Given the large sample size and the smooth functional form linking estimated first-stage moments to $\hat{\rho}_{h,t}$, the additional uncertainty from estimation is expected to be small. Nonetheless, to verify robustness, we re-estimate the main panel regressions using bootstrap-based standard errors (100 replications), both with and without analytical weights proportional to $1/\sqrt{\hat{\sigma}^2_{h,t}}$, which yielded virtually identical results. This supports the interpretation that inference is not materially affected by generated-regressor uncertainty.

Regarding the expected sign of our coefficient of interest ($\hat{\omega}$), our working hypothesis is as follows. Because program targeting prioritizes more vulnerable households, contemporaneous estimates of assistance effects may be attenuated. Consequently, the estimated coefficients should be interpreted as lower-bound associations rather than precise causal effects. In this context, if (i) $\hat{\omega}$ is consistently positive and significant across all specifications; (ii) no anticipatory (lead) effects are detected; and (iii) quantile regressions reveal a significantly positive but declining effect across the resilience distribution, then the evidence can be interpreted as supporting the existence of a genuine positive association between contemporaneous assistance and resilience. While we cannot claim strict causal identification, the robustness of the results and their consistency with theoretical expectations might warrant a causal reading, subject to the caveat of residual endogeneity.

6. Results

In this section, we first discuss the outcomes of resilience estimation. Next, we investigate how the estimated resilience is distributed across Governorates, waves, and population groups. Finally, we explore how household resilience is statistically associated with dependence on unconditional cash assistance.

[10] Estimation is done for both a linear regression and a fractional-logit specification. Since results are nearly identical, all results below refer to the linear model.

[11] The estimated autocorrelation coefficient for $\hat{\rho}_{h,t}$ is 0.723 (0.551 if one partials out household controls $X_{h,t}$).

Table 3
Estimated margins for first- and second-moment regressions. Significance: * = 0.10; ** = 0.05; *** = 0.01. GLM: Generalized linear model with log link. Governorate Dummies: YES. Wave dummies: NO. Robust SE clustered at Governorate level in parentheses.

	First moment						Second moment	
	OLS		GLM		POISSON		POISSON	
	(1) SMEB	(2) INCOME	(3) SMEB	(4) INCOME	(5) SMEB	(6) INCOME	(7) SMEB	(8) INCOME
Lagged SMEB	0.386***	–	0.339***	–	0.304***	–	−0.079***	–
	(0.018)	–	(0.018)	–	(0.015)	–	(0.022)	–
Lagged Income	–	0.504***	–	0.451***	–	0.444***	–	−0.068***
	–	(0.012)	–	(0.019)	–	(0.017)	–	(0.008)
Head Old	−0.038**	−0.016	−0.041***	−0.032	−0.063***	−0.033**	0.001	0.006
	(0.015)	(0.015)	(0.016)	(0.021)	(0.015)	(0.016)	(0.044)	(0.006)
Head Married	−0.060*	0.036**	−0.075**	0.002	−0.061**	−0.001	−0.026	−0.048***
	(0.030)	(0.014)	(0.032)	(0.015)	(0.029)	(0.018)	(0.029)	(0.013)
Head Educated	0.073***	0.035***	0.071***	0.041***	0.101***	0.068***	−0.044	0.016**
	(0.016)	(0.011)	(0.013)	(0.008)	(0.012)	(0.008)	(0.027)	(0.007)
Syrian	−0.004	−0.072***	−0.049***	−0.027*	−0.036**	−0.016*	0.078***	−0.050***
	(0.014)	(0.020)	(0.015)	(0.014)	(0.014)	(0.009)	(0.019)	(0.014)
Size	−0.052***	−0.054***	−0.060***	−0.061***	−0.078***	−0.069***	−0.035***	−0.026***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.002)	(0.004)
Head Disability	−0.041*	−0.011	−0.022	−0.027	−0.047**	−0.048*	0.033	−0.025***
	(0.019)	(0.023)	(0.022)	(0.027)	(0.022)	(0.027)	(0.030)	(0.008)
Eviction Threats	−0.212***	−0.125***	−0.171***	−0.144***	−0.179***	−0.140***	0.118***	−0.006
	(0.019)	(0.016)	(0.011)	(0.010)	(0.010)	(0.010)	(0.041)	(0.012)
Amman Govt	0.079***	0.135***	0.161***	0.202***	0.097***	0.176***	0.210***	0.029***
	(0.005)	(0.009)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)
No. Obs.	7410	7208	7538	7385	7385	7385	7410	7208
R^2	0.207	0.374	–	–	–	–	–	–
Adj R^2	0.205	0.372	–	–	–	–	–	–
BIC	17,536.93	12,512.61	70,480.39	73,140.7	181,705.3	170,731.7	17,330.11	10,221.82
AIC	17,460.92	12,450.66	70,404.19	73,078.53	181,629.1	170,669.5	17,254.09	10,159.88

6.1. Estimation of household resilience: marginal conditional distributions

We first observe that all estimated margins for the first moment of conditional livelihood indicators, as reported in Table 3, col. 1–6, are fairly stable across three alternative estimation techniques: OLS, GLM and Poisson.[12] This suggests that OLS can be retained as our benchmark estimator. Second, the lagged values of livelihood indicators positively and significantly affect the dependent variable, as expected. Furthermore, both household SMEB and INCOME are negatively impacted by household size and threats of eviction, while they increase if household head is educated and if the household is located in the Amman Governorate. Overall, households with an older head and Syrian nationality tend to display worse livelihood conditions, although those factors are less statistically prominent.

Results related to the margins of the second moment indicate that a better lagged livelihood tends to dampen the conditional variance. Conversely, the conditional second moment of livelihood indicators is amplified if the household is Syrian and lives in the Amman Governorate (Table 3, col. 7–8).

Predictions for the first and second conditional moments of our two marginal livelihood indicators are then employed to estimate their distributions. As mentioned above, we assume that SMEB and INCOME are marginally distributed either as a log-normal or a Gamma. Using the SMEB and INCOME exogenous minimal thresholds, we therefore end up, for each household, with four resilience probabilities in wave $t = \{2, 3, 4\}$: SMEB (log-normal vs. Gamma) vs. INCOME (log-normal vs. Gamma). The scatter plots of household resilience probabilities $\hat{\rho}$ estimated for both SMEB and INCOME using either a log-normal or a Gamma density, shown in Figs. B1 and B2 in Appendix B, clearly indicate that the two measures of resilience are positively and strongly correlated—Pearson correlation coefficients in the pooled sample read 0.9141 for SMEB and 0.9981 for INCOME. This robustness check indicates that one can safely focus on the log-normal assumption only without losing much information. Note that assuming that marginal livelihood indicators are conditionally distributed as a log-normal allows for more analytical tractability, which will be very useful when we compute a joint measure of resilience (more on this below).

Since SMEB and INCOME are positively correlated across households in each wave and in the pooled sample, we expect that also the estimated marginal resilience probabilities $\hat{\rho}$ display some positive association across households. This is confirmed by the scatter plots in Fig. 3, which also suggest that, across waves and in the pooled sample, household resilience probabilities for INCOME are much more dispersed in the unit interval than those for SMEB. To get a better feel of how the two resilience measures are intertwined, Fig. B3 in Appendix B shows their quantile-quantile plots. Overall, those two sets of graphs indicate that, for probability values below some threshold $\rho^* \sim 0.60$, households are more resilient in the SMEB dimension than in the income one, while the opposite holds if probabilities are larger than that threshold, where household tend to display more similar and larger resilience levels in both dimensions. This is not surprising, as refugee households in our database exhibit a larger and more dispersed propensity to consume in basic items when their income is not always enough to meet sufficient standards, leading to a marginally higher resilience in SMEB than in income. Instead, when income increases, we expect households to be resilient in both dimensions, also as a result to the marginal decrease in the propensity to consume basic items for larger income. The above results also suggest that, beside the more natural threshold $\rho^* = 0.50$, one

[12] Margins allow for comparability of estimates across the three models, in the first of which the dependent variable (and lags thereof) enters in logs, while in the other two in levels.

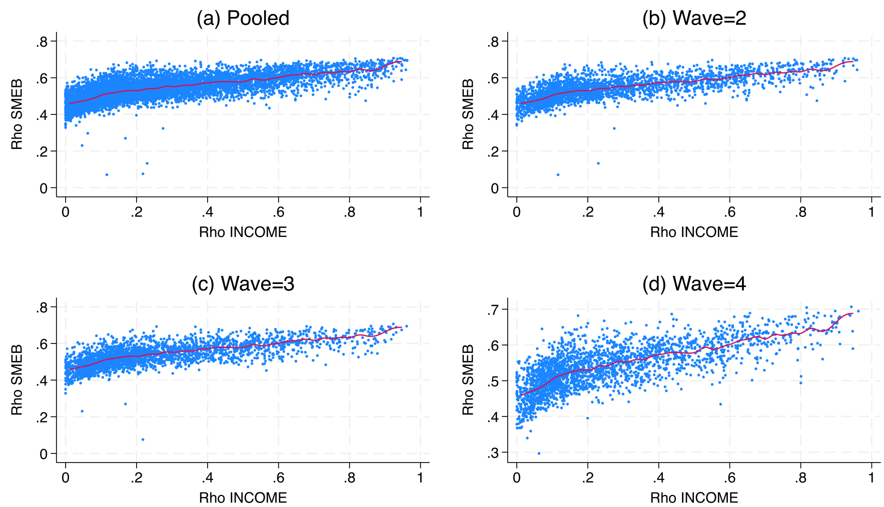

Fig. 3. Scatter plots of log-normal $\hat{\rho}$ SMEB vs $\hat{\rho}$ INCOME across waves and in the pooled sample.

may also employ $\rho^* = 0.60$ an alternative to deem household as being resilient or not—as we will do below.[13]

6.2. Estimation of household resilience: joint conditional distribution

The foregoing evidence indicates that employing marginal probabilities $\hat{\rho}$ for SMEB and INCOME as they come from two statistically independent uni-variate conditional random variables might convey a biased estimate of household joint resilience in the (SMEB, INCOME) space. A better proxy for joint resilience can instead be obtained by positing that SMEB and INCOME are distributed as a bi-variate log-normal, i.e., that their logs follow a bi-variate Gaussian. Estimates for first and second conditional marginal moments are already available from the regressions in Table 3. Following the procedure sketched in Section 5.2, we obtain an estimate for the conditional correlation coefficient and therefore fully characterize the joint conditional bi-variate distribution (SMEB, INCOME).[14] This allows us to employ both our exogenous minimum livelihood standards defined earlier for SMEB and INCOME, and end up with an estimate for joint household-resilience conditional probabilities.

Descriptive statistics for our final measures of household resilience probabilities $\hat{\rho}$ (SMEB, INCOME, JOINT), reported in Table A3, Appendix A, show that joint resilience is more strongly (partially) associated with INCOME than with SMEB, although a simple OLS regression of $\hat{\rho}$ JOINT against $\hat{\rho}$ SMEB and INCOME (with waves and Governorate dummies included) points out that they contribute almost equally to our joint estimate of household resilience—see also the 3-dimensional scatter plot of $\hat{\rho}$ (SMEB, INCOME, JOINT) in Fig. B5.

Furthermore, we observe that JOINT resilience is more strongly and positively correlated with marginal resilience to INCOME than with SMEB, as suggested by the different dispersion of the clouds depicted in Figs. 4 and 5. As discussed above, this behavior might be driven by the fact that as income decreases, consumption for SMEB becomes more volatile, and so does the propensity to consume for SMEB.

Taken together, the foregoing evidence seems to suggest that accounting for the correlation between well-being indicators in estimating a joint measure of resilience may have some impact on predicted shares of resilient households, once some exogenously given probability thresholds are provided, and may potentially improve the precision of such estimates as compared to the case where resilience is computed assuming uncorrelated well-being indicators.

6.3. Household resilience across governorates, waves, and population groups

In the following, we explore the properties of estimated household resilience distributions conditioning them on: (i) Governorates' per-capita income and population density; (ii) waves; and (iii) relevant refugee groups, as detailed below. Data about year-2022 Governorate population, per-capita income (in current JOR), and area (in square kilometers), is retrieved from the Jordan Department of Statistics (DoS, cf. dosweb.dos.gov.jo).

Scatter plots of the average of our $\hat{\rho}$ JOINT estimates against Governorate population density and income, as displayed in Figs. 6 and 7, clearly indicate that household resilience probabilities decrease with Governorate population density and increase with Governorate income. Similar results hold for marginal probabilities $\hat{\rho}$ SMEB and INCOME. Therefore, refugee households that live in higher-income or low population-density Governorates on average display a larger resilience. Admittedly, household self-selection into Governorates may give rise to endogeneity and selection bias, implying that observed geographic differences in resilience should be interpreted primarily as descriptive rather than causal. This is most likely because, beyond initial displacement, many refugees actively choose their place of residence based on family ties, economic opportunities, and infrastructure (Bove et al., 2022; Loewe, 2020; Tyldum & Zhuang, 2023). Although only 6% of households in our panel changed Governorate within 2022, self-selection at first settlement may remain a concern.

In order to study how household resilience probability distributions change over time and population groups, we begin by defining a refugee household h as "resilient" if its estimated $\hat{\rho}_{h,t}$ in wave t is larger than a threshold ρ^* in either of the three dimensions SMEB, INCOME and JOINT. We then compute the percentage of resilient household across waves. As Table 4 shows for two relevant thresholds $\rho^* \in \{0.50, 0.60\}$, refugee households have become less resilient across the quarters of year 2022. This happens not only for marginal resilience probabilities (SMEB

[13] We stress that the normative probability thresholds $\rho^* = 0.50$ and $\rho^* = 0.60$ are applied solely for classifying households as "resilient" in the computation of descriptive percentages, cf. Tables 4 and 5. All other analyses use the continuous resilience probability estimates without dichotomization. The choice of these values follows prior literature (e.g., Cissé & Barrett, 2018; Vaitla et al., 2020) and is inherently normative, as $\hat{\rho}$ values are probabilities by construction. Results are robust to alternative thresholds, within reasonable ranges, as discussed below.

[14] Fig. B4 in Appendix B reports its distribution in the case of the pooled sample together with a Gaussian fit, from which we appreciate once again the underlying positive association of conditional livelihood indicators.

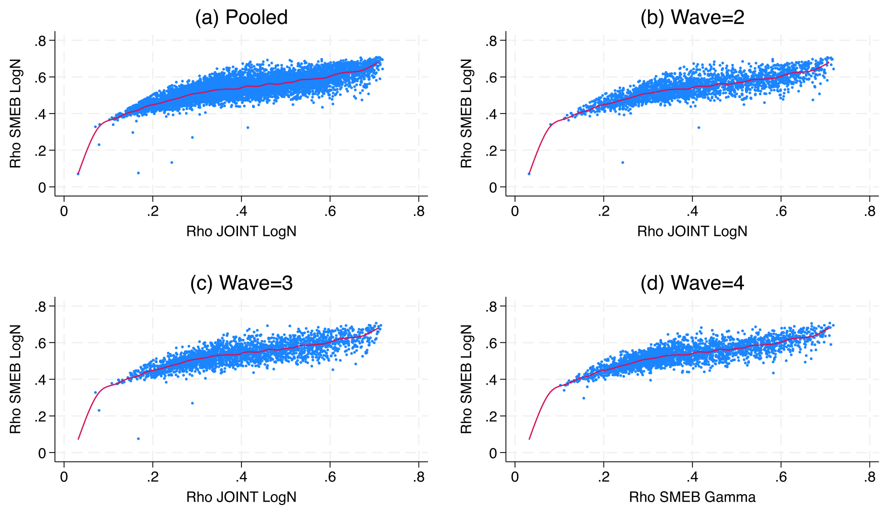

Fig. 4. Scatter plots of log-normal $\hat{\rho}$ SMEB vs $\hat{\rho}$ JOINT across waves and in the pooled sample.

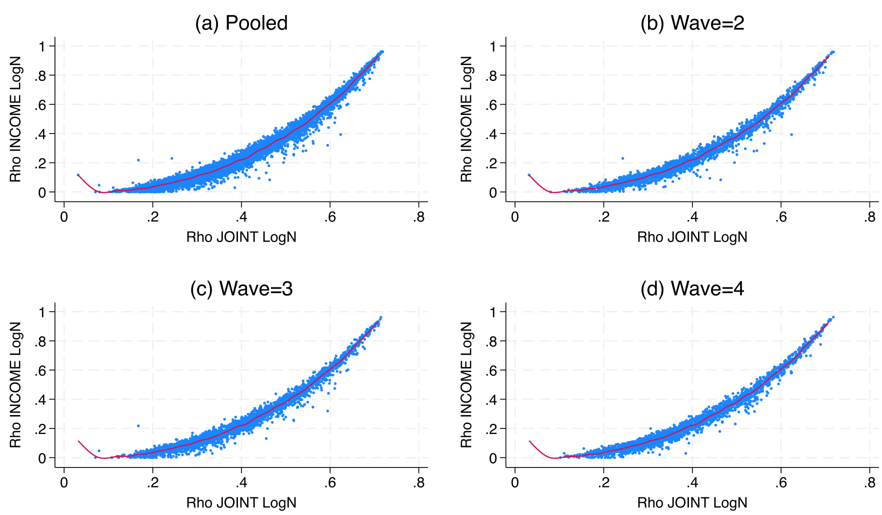

Fig. 5. Scatter plots of log-normal $\hat{\rho}$ INCOME vs $\hat{\rho}$ JOINT across waves and in the pooled sample.

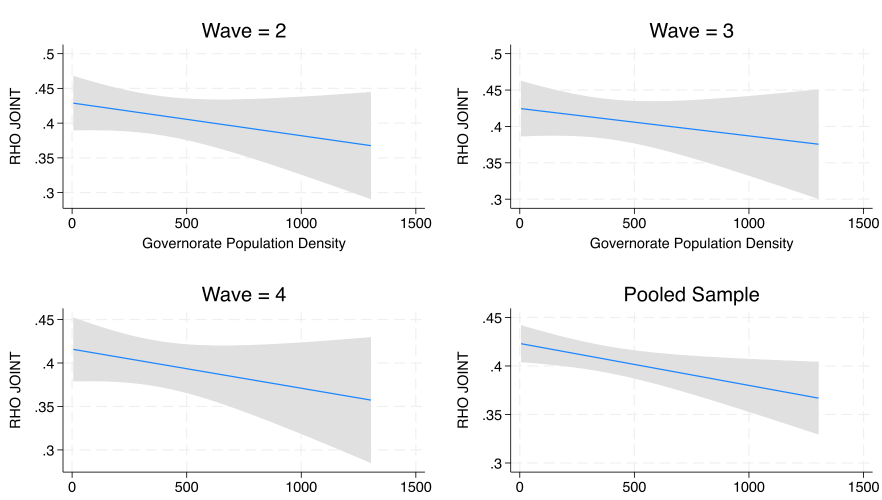

Fig. 6. Linear fit of $\hat{\rho}$ JOINT distributions vs Governorate population density in year 2022, across waves and in the pooled-sample. 95% confidence bands in grey.

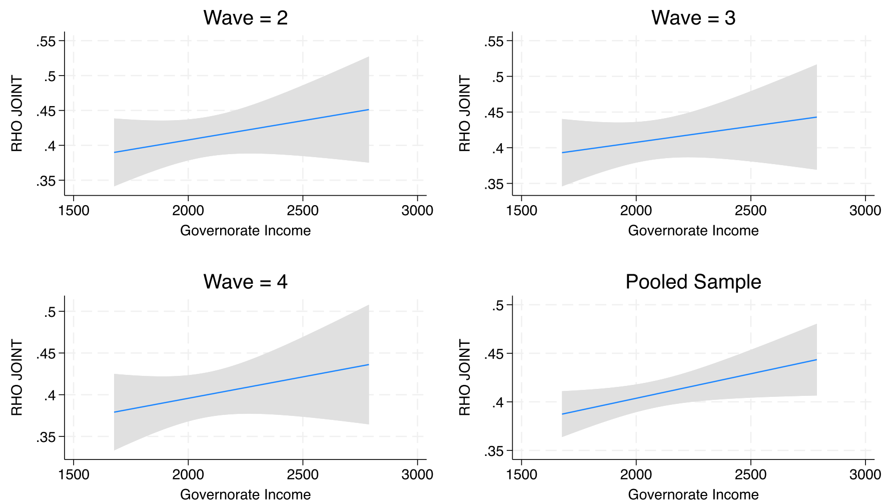

Fig. 7. Linear fit of $\hat{\rho}$ JOINT distributions vs governorate (per capita) income in year 2022, across waves and in the pooled-sample. 95% confidence bands in grey.

Table 4
Percentage of resilient households ($\hat{\rho} > \rho^*$) across waves at two alternative probability thresholds $\rho^* \in \{0.50, 0.60\}$.

$\rho^* = 0.50$			
Wave	SMEB	INCOME	JOINT
2	74.1%	23.7%	34.3%
3	72.7%	22.4%	32.4%
4	70.2%	20.1%	31.4%
$\rho^* = 0.60$			
Wave	SMEB	INCOME	JOINT
2	23.1%	17.6%	19.0%
3	22.0%	16.1%	17.7%
4	21.3%	14.3%	16.2%

and INCOME), but also jointly (JOINT). This confirms our inspection of descriptive statistics for $\hat{\rho}$ (SMEB, INCOME, JOINT), cf. Table A3, suggesting that both their means and medians have been slightly decreasing across waves. This is consistent with UNHCR reports, which indicate a decline in the total average monthly expenditure along with a deterioration in the perception of household financial situation throughout the 2022 waves (UNHCR, 2023b). Moreover, only about 20% of households display a reasonably high resilience probability ($\rho^* = 0.60$). Furthermore, as expected from our discussion in Sections 6.1 and 6.2, the percentage of households characterized by even larger $\hat{\rho}$'s drops to extremely small figures very quickly. For example, additional computations show that only about 9% of households display joint resilience probabilities larger than 0.70 in the first wave, and only about 7% in the fourth wave. Overall, our estimates indicate that refugee households in Jordan were already far from achieving and maintaining an acceptable level of well-being at the beginning of 2022. The observed decline in refugee household resilience throughout the year likely reflects the compounding effects of several interrelated macroeconomic and humanitarian stressors. First, inflationary pressures-particularly in food and energy-were substantial: Jordan's annual consumer price index rose by 4.2% in 2022, with food prices increasing by over 5.6% (The World Food Program, 2022). These price shocks disproportionately affected vulnerable refugee households, whose income and consumption levels are highly sensitive to such fluctuations. Second, although UNHCR and WFP funding levels remained volatile rather than systematically declining, both agencies reported shortfalls and coverage constraints that limited or delayed cash and food assistance for some refugee households during 2022 (UNHCR, 2022b). Such funding uncertainty likely compounded the impact of inflationary pressures. Third, the lingering effects of the COVID-19 pandemic continued to weigh on refugee livelihoods. While not worsening in 2022, labor market recovery remained incomplete, particularly for informal and refugee workers, many of whom faced unstable employment and unmet health needs (Kattaa et al., 2022; UNHCR, 2023a). Fourth, persistent water scarcity and service constraints continued to affect household well-being, particularly among refugees residing in resource-stressed areas (Unicef, 2022). Finally, recurrent political and institutional tensions-though not markedly escalating-maintained an environment of uncertainty and limited fiscal space for refugee-hosting communities.[15] Taken together, these conditions provide a plausible contextual backdrop for the decline in measured resilience during 2022, with price shocks and assistance volatility likely playing the most immediate roles. This highlights the importance of monitoring resilience as a dynamic metric sensitive to evolving vulnerability drivers.

From a methodological perspective, inspection of Table 4 indicates that predicting the shares of resilient households may improve in precision if one employs a joint conditional probability approach, as compared to treating well-being indicators as they were independent. Indeed, notice that at both threshold levels ρ^*, joint shares lie always in between the correspondent percentages computed using either SMEB or INCOME only, which would result in a persistent over- or under-estimation. To double check, we have also computed the percentage of resilient households that both have resilient probabilities larger than ρ^*, but without accounting for correlation as in the joint case. Those range between 19.2% and 22.4% when $\rho^* = 0.50$ and between 10.2% and 11.3% when $\rho^* = 0.60$ across waves, thus resulting in a strong under-estimation in comparison with joint estimates.

Finally, we evaluate the differences between percentages of "resilient" households across some relevant refugee groups, i.e. households located in the Amman Governorate vs. those located elsewhere; Syrian refugee households vs. households of other nationalities; households eligible (vs. not) to receive cash from either WFP or UNHCR and enrolled in (vs. phased out from) WFP's assistance initiatives. The Z-scores for the two-sided test of differences between percentages, reported in Table 5, indicate that, robustly over two relevant probability thresholds $\rho^* \in \{0, 50, 0.60\}$, the percentage of "resilient" households is larger if they are located in Amman; if they are of nationalities other than the Syrian one; and if they are either not cash eligible or not enrolled in WFP's assistance programs. Notice, however, that this sort of negative

[15] Cf. for example https://www.hrw.org/world-report/2023/country-chapters/jordan.

Table 5
Testing for the difference in % of resilient households between groups at two alternative probability thresholds $\rho^* \in \{0.50, 0.60\}$. Z-scores and significance ($^* = 0.10$; $^{**} = 0.05$; $^{***} = 0.01$) of two-sided tests (H_0 : equal percentages).

Wave	$\rho^* = 0.50$			$\rho^* = 0.60$		
	SMEB	INCOME	JOINT	SMEB	INCOME	JOINT
Household In Amman vs Not In Amman						
2	8.910***	1.200*	2.210**	4.187***	1.263*	1.967**
3	9.020***	1.880*	3.500***	2.854***	1.239*	1.192*
4	10.190***	2.260**	2.820***	4.130***	1.423*	1.130*
Syrian Household vs Non Syrian Household						
2	−3.750***	−0.800**	−2.540**	−4.423***	−1.564*	−1.044*
3	−2.080**	−0.610*	−1.800*	−3.654***	−1.373*	−1.063*
4	−2.760***	−1.220**	−0.620*	−4.342***	−2.366**	−1.970**
Cash Eligible vs Not Eligible Household						
2	−3.967***	−1.344	−1.981**	−1.898*	−3.565***	−3.899***
3	−2.226**	−1.792*	−1.335	−1.978**	−2.660***	−3.584***
4	−1.179	−3.150***	−1.807*	−1.860*	−5.267***	−5.266***
Household in WFP vs Household Not in WFP						
2	−5.130***	−10.941***	−12.496***	−4.597***	−10.563***	−10.189***
3	−5.416***	−11.263***	−11.857***	−4.124***	−10.009***	−9.493***
4	−6.104***	−8.226***	−9.755***	−4.123***	−6.300***	−6.931***

link with assistance is stronger for households receiving assistance than it is for those only eligible to receive cash. Also, the negative association between cash eligibility and percentage of "resilient" households becomes stronger for households whose resilience probabilities are larger ($\rho^* = 0.60$).

Whereas the evidence on geography is in line with what is observed above about the correlation between resilience and Governorates' income (cf. Fig. 7), the relationship between resilience and assistance likely reflects the institutional design of UNHCR and WFP programs in Jordan, where transfers are explicitly targeted to the most vulnerable households through structured vulnerability assessments (see Sections 2 and 5.3). Since households with lower resilience are systematically more likely to receive support, purely descriptive associations risk substantial downward bias. As a result, negative correlations should not be mistaken for the true effect of assistance on resilience.

6.4. Resilience probabilities and dependence on cash assistance

To dig deeper into the relationship between assistance and resilience among refugee households, we estimate a battery of panel regressions and conduct robustness checks, as outlined in Section 5.3. Our main results are reported in Table 6. Each column corresponds to a different model specification, depending on whether the lag of the dependent variable and/or household-specific time trends are included, as indicated in the "Specification panel" at the bottom.[16]

Across all assistance variables, estimates are consistently positive and statistically significant. Importantly, the estimated contemporaneous effect of assistance increases once we control for persistence in household resilience, suggesting that specifications without lagged outcomes—columns (1) and (2)—may suffer from downward bias due to the negative correlation between past resilience and current assistance. In this sense, estimates in column (2) are plausibly closer to the true contemporaneous effect. The inclusion of linear trends confirms this pattern: margins remain positive and significant, and in most cases increase in magnitude—cf., columns (3) and (4). These trends absorb slow-moving household-level factors that may correlate with both assistance and resilience—such as omitted determinants of targeting—thus reinforcing the interpretation of a robust association between dependence on assistance and resilience. Taken together, the evidence supports a causal interpretation under reasonable assumptions, while acknowledging possible residual endogeneity.

We also find no evidence of anticipatory effects: leads of assistance ($A_{i,t+1}$) are insignificant across specifications, whether included alone or jointly with contemporaneous treatment (columns 5–8). This reduces concerns about pre-trends, since systematic anticipation of transfers—e.g., households adjusting resilience-related behavior in advance—would likely generate significant pre-treatment effects. Moreover, when leads are introduced alongside contemporaneous assistance, the latter remains positive and significant, lending credibility to a contemporaneous causal interpretation.

Next, we examine whether the contemporaneous impact of assistance on resilience varies across levels of household dependence on assistance. To this end, we estimate panel regressions in which the "Dependence on Assistance Ratio" enters quadratically on the right-hand side and visualize results using a marginal-effect plot. Across all specifications, two findings emerge: (i) the effect of assistance on resilience is positive and statistically significant throughout the entire range of dependence; and (ii) the magnitude of this effect increases as households become more dependent on assistance—cf. Fig. 8 for an example using specification (2) in Table 6. In other words, households that rely more heavily on assistance experience larger gains in resilience than those receiving less support, an outcome broadly consistent with the design of humanitarian aid programs in Jordan, which prioritize the most vulnerable. Furthermore, taken together with earlier results, this pattern suggests that the estimated positive association between assistance and resilience remains robust across specifications. Given the negative targeting mechanism, the magnitude of the estimates is consistent with the possibility that targeting may attenuate the observed contemporaneous association. However, our empirical design does not allow us to formally establish whether the coefficients represent lower bounds of the causal effect.

Finally, we conduct a quantile regression analysis to assess whether dependence on assistance ("Dependence on Assistance" = 1) has heterogeneous effects across the household resilience distribution. Across all main specifications, we find a smoothly declining pattern: the estimated effect is positive and significant at all quantiles but largest at the lower end of resilience, gradually decreasing as resilience rises (see Fig. 8, Column (2)). This suggests that the marginal benefit of cash assistance is heterogeneous and concentrated among the households that need it most, consistent with program design. These results also shed light on targeting bias and endogeneity. Because program rules direct assistance toward less resilient households, negative selection may be particularly relevant at the lower tail of the resilience distribution, potentially attenuating estimated associations where resilience is lowest. The fact that estimated coefficients remain positive and statistically significant across quantiles (and are largest among the least resilient households) is consistent with the presence of heterogeneous associations aligned with program design. While this pattern is not easily explained by a pure selection mechanism alone, our empirical strategy does not allow us to formally disentangle reactive targeting from contemporaneous assistance effects. The results should therefore be interpreted as evidence of heterogeneous within-household associations, potentially consistent with diminishing marginal returns, while acknowledging residual endogeneity.

Two additional notes are in order. The first concerns the Cash Eligibility and WFP dummies included among controls. These variables capture households' eligibility status and participation in assistance schemes, determined by UNHCR and WFP targeting rules prior to each survey wave and thus largely predetermined. As shown in Section 4, they display limited within-household variation: about 70–75 percent

[16] All specifications use predicted household resilience $\hat{\rho}$ JOINT as the dependent variable and are estimated with household fixed effects and standard errors clustered at the household level; see Section 5.3 for details.

Table 6
Results from panel-regression exercises. Dependent variable: estimated household-resilience probabilities ($\hat{p}$ JOINT). All specifications include wave dummies, fixed effects at the household level and household controls (cf. Section 5.3). Each margin cell in the table reports the estimate for a separate regression where the corresponding assistance variable is included alone. Standard errors are clustered at the household level. Significance: *** 0.01, ** 0.05, * 0.10.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Assistance Variable	Contemporaneous Margin							
Dep Assistance Ratio Binary	0.018***	0.025***	0.036***	0.178***	–	–	0.022***	0.030***
	(0.003)	(0.004)	(0.005)	(0.001)			(0.003)	(0.004)
Dep Assistance Ratio (linear)	0.034***	0.058**	0.077***	0.078***	–	–	0.040***	0.063***
	(0.005)	(0.006)	(0.008)	(0.019)			(0.005)	(0.006)
Dep Assistance Ratio (squared)	0.030***	0.054***	0.072***	0.232***	–	–	0.036***	0.060***
	(0.005)	(0.007)	(0.009)	(0.019)			(0.005)	(0.008)
Rent Assistance	0.013**	0.018***	0.036*	0.041***	–	–	0.014**	0.034**
	(0.006)	(0.003)	(0.003)	(0.001)			(0.006)	(0.015)
Assistance Variable	Lead Margin							
Dep Assistance Ratio Binary	–	–	–	–	0.002	0.001	0.003	0.004
					(0.001)	(0.001)	(0.002)	(0.003)
Dep Assistance Ratio (linear)	–	–	–	–	0.001	0.002	0.001	0.001
					(0.001)	(0.002)	(0.001)	(0.001)
Dep Assistance Ratio (squared)	–	–	–	–	0.001	0.001	0.002	0.001
					(0.001)	(0.001)	(0.002)	(0.001)
Rent Assistance	–	–	–	–	0.001	0.000	0.000	0.006*
					(0.001)	(0.001)	(0.001)	(0.003)
Specification								
Lag of Dependent Variable	NO	YES	NO	YES	NO	YES	NO	YES
Household-Specific Time Trends	NO	NO	YES	YES	NO	NO	NO	NO

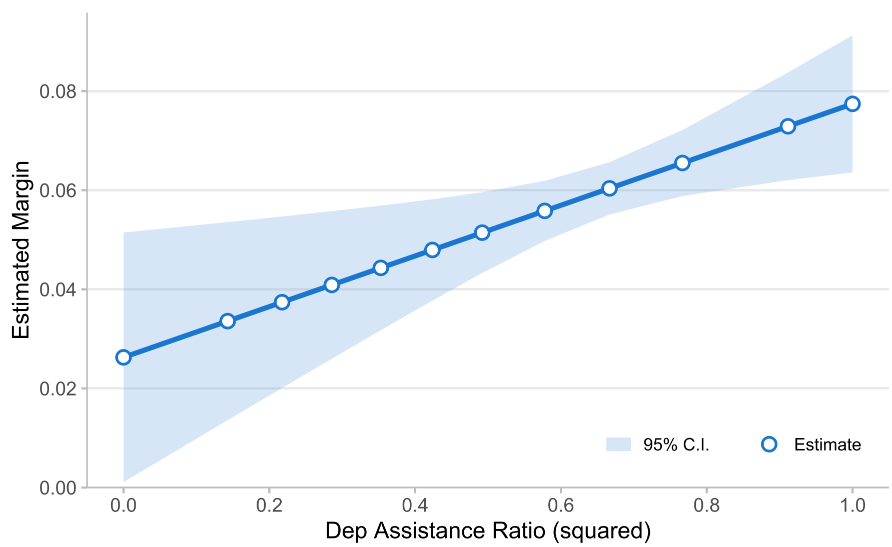

Fig. 8. Margins plot for the impact of "Dep assistance ratio (squared)" on household resilience ($\hat{p}$ JOINT) in a panel-regression specification as in Eq. (6), cf. Column (2) of Table 6.

of households retain the same value (0 or 1) for three or four consecutive quarters, and frequencies remain stable across waves. With fixed effects included, most of this variation is absorbed. Consistently, excluding these dummies leaves the assistance coefficient virtually unchanged, confirming that their inclusion does not bias results but strengthens robustness.

The second remark concerns the interpretation of the estimated within-household effects. Given the fixed-effects specification, identification arises from changes within the same household over time, including both transitions into assistance and transitions out of assistance. The positive contemporaneous association between assistance and resilience therefore reflects within-household variation over time in the joint occurrence of assistance receipt and resilience outcomes. However, this specification does not allow us to distinguish whether the estimated association reflects improvements during assisted periods, relatively lower resilience during non-assisted periods, or the timing of assistance relative to shocks and subsequent recovery. In targeted programs, where assistance responds to evolving vulnerability, these mechanisms are inherently difficult to disentangle. The estimates should therefore be interpreted as within-household associations between assistance receipt and resilience, without attributing a specific direction of change.

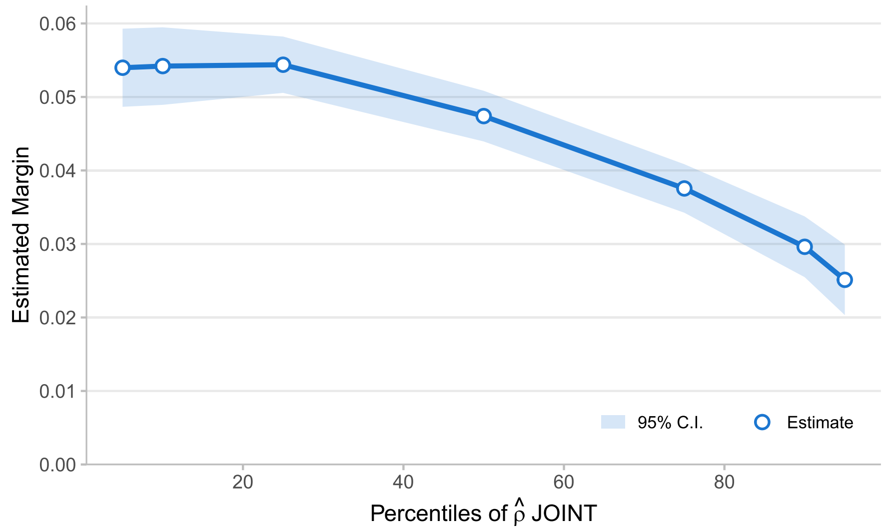

Fig. 9. Impact of "Dep assistance ratio binary" on household resilience ($\hat{\rho}$ JOINT) percentiles (x-axis) in a quantile regression whose specification is as in Eq. (6), cf. Column (2) of Table 6.

7. Discussion and conclusions

Leveraging UNHCR data from the "Quarterly Assessment of the Socio-Economic Situation of Refugees", this paper explored refugee household resilience in Jordan across the four quarters of 2022. Using the Cissé–Barrett (CB) framework, which conceives resilience as a normative condition, we estimated the probability that households maintain a minimum standard of well-being, conditional on lagged livelihood outcomes and additional controls. A key methodological contribution is the computation of the joint conditional probability that households meet acceptable thresholds in both income and expenditure (SMEB) dimensions—thus improving the precision and interpretability of resilience estimates relative to single-indicator approaches.

To the best of our knowledge, this is among the first quantitative applications of the CB framework to refugee populations. Most prior studies focus on rural or food security contexts rather than forced displacement. The only comparable work for Jordan is an FAO report (FAO, 2018) relying on a 2013 cross-sectional dataset and a non-normative index-based approach (RIMA-II).

Our results highlight three key insights. First, accounting for the correlation between income and expenditure improves precision in resilience estimates. Second, refugee households residing in higher-income or less densely populated Governorates exhibit greater resilience, while overall resilience declined across the four quarters of 2022. Third, we find a robust positive contemporaneous association between cash assistance and household resilience, consistent across specifications controlling for fixed effects, clustered errors, lagged outcomes, and household-specific trends. The effect is strongest among households most dependent on assistance and those at the lower end of the resilience distribution, indicating that transfers reach those most in need.

Although targeting bias and reverse causality cannot be entirely ruled out, the robustness and internal consistency of the results strengthen confidence in the stability of the estimated associations across specifications. Given the negative targeting structure, residual bias may influence the magnitude of the estimates. However, our empirical design does not allow us to formally determine its direction. This interpretation follows a common tradition in applied development economics, whereby assignment bias is recognized as an inherent feature of targeted programs but is not viewed as invalidating the results. In this literature, negative correlations are commonly read as evidence that programs successfully reach vulnerable households rather than as proof that transfers are harmful (Dehejia & Wahba, 1999; Ravallion & Chen, 2005). At the same time, the presence of robust contemporaneous effects and theory-consistent heterogeneity patterns—stronger impacts for poorer or more vulnerable households—are commonly interpreted as being consistent with genuine program impacts (cf., *inter alia*, Banerjee et al., 2015; Haushofer & Shapiro, 2016).

Our findings add to a growing body of evidence suggesting that unconditional cash assistance can be positively associated with stronger household resilience, both in Jordan and in other vulnerable contexts (Gassmann et al., 2023). Viewed collectively, both contemporaneous effects and the systematic quantile gradients we document are consistent with humanitarian aid functioning as intended, namely by supporting those most in need. This aligns with the broader literature showing that well-designed transfers not only smooth consumption and meet immediate needs but can also enhance adaptive capacity, social connectedness, and resilience trajectories (Abu Hamad et al., 2025; Mahrt et al., 2025). At the same time, our results should be read against evidence pointing to possible unintended consequences, such as dependency risks, debt reliance, or local market distortions (Della Guardia et al., 2022; Oconnor, 2024; Premand & Stoeffler, 2020). Overall, our analysis supports a cautious interpretation of cash assistance as a critical safety net and resilience-building tool, provided that it remains effectively targeted and is accompanied by complementary interventions (Gupta et al., 2024; Kondylis & Loeser, 2021).

A central limitation of our analysis concerns the restricted inclusion of explicit household-level shocks. The econometric specification incorporates only one idiosyncratic shock proxy—the "Eviction Threat" variable—which may not be fully exogenous. The dataset lacks consistent measures of other shocks (e.g., health crises, job losses, or price spikes), while external sources offer only coarse spatial data. This absence limits the ability to distinguish vulnerability from persistent deprivation and points to the need for improved longitudinal shock data in future surveys. In light of these limitations, incorporating indicators of realized shocks and recovery dynamics remains a priority for future research, which would allow a more comprehensive assessment of household resilience in displacement settings.

Beyond measurement issues, richer and longer panels would enable stronger causal inference and a clearer separation between assistance effects and unobserved household dynamics. More granular information—such as on employment, gender, food consumption, and asset ownership—would allow multidimensional resilience estimation and finer heterogeneity analysis. At the same time, external validity is context-dependent: Jordan's refugee response benefits from relatively advanced delivery systems, targeting instruments, and sustained international support, conditions that may not generalize to other low-resource settings. Comparative applications of this framework to other refugee datasets (e.g., Ethiopia, Uganda, Malaysia) could test robustness and policy transferability.

Finally, future research could extend this framework by linking resilience dynamics to program duration and transition outcomes—distinguishing short-term stabilization from long-term self-reliance. Conditional assistance schemes, though rare in Jordan, could also be compared to unconditional cash to assess complementarities between protection and activation mechanisms. Expanding the set of livelihood indicators beyond monetary dimensions would further enhance the multidimensional scope of resilience measurement.

Overall, our findings underscore the importance of sustained, well-targeted assistance as a welfare-stabilizing mechanism and as a factor consistently associated with stronger resilience outcomes in protracted displacement contexts. At the same time, they highlight the need for better data, refined methods, and integrated policy frameworks to capture the complex, evolving nature of refugee resilience.

CRediT authorship contribution statement

Giorgio Fagiolo: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Marina Mastrorillo:** Writing – review & editing, Resources, Methodology, Investigation, Data curation, Conceptualization. **Grazia Pacillo:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Additional tables

See Tables A1–A3.

Table A1
Number and percentage of households in each Governorate, by waves and in the pooled sample.

Governorate	Wave 1	2	3	4	Pooled sample
Ajloun	22	22	23	22	89
	0.8%	0.8%	0.9%	0.8%	0.8%
AlBalqa	99	87	84	86	356
	3.8%	3.3%	3.2%	3.3%	3.4%
AlKarak	39	34	36	35	144
	1.5%	1.3%	1.4%	1.3%	1.4%
Amman	1271	1306	1303	1301	5181
	48.3%	49.6%	49.5%	49.4%	49.2%
Aqaba	53	52	52	58	215
	2.0%	2.0%	2.0%	2.2%	2.0%
Zarqa	239	225	225	229	918
	9.1%	8.6%	8.6%	8.7%	8.7%
Irbid	399	389	402	406	1596
	15.2%	14.8%	15.3%	15.4%	15.2%
Jerash	38	33	37	36	144
	1.4%	1.3%	1.4%	1.4%	1.4%
Maan	84	87	87	83	341
	3.2%	3.3%	3.3%	3.2%	3.2%
Madaba	71	69	67	61	268
	2.7%	2.6%	2.5%	2.3%	2.5%
Mafraq	301	311	297	297	1206
	11.4%	11.8%	11.3%	11.3%	11.5%
Tafila	15	16	18	17	66
	0.6%	0.6%	0.7%	0.6%	0.6%
Total	2631	2631	2631	2631	10,524

Table A2
List, type, and description of the variables employed in the analysis. Notes: (†) Please refer to main text for more details on variable definitions.

Variable name	Type	Description
Governorate	Binary	Governorate Name
Head Old	Binary	= 1 if head age > 50 yrs
Head Married	Binary	= 1 if head is married
Head Educated	Binary	= 1 if head ever attended at least secondary school
Head Disability	Binary	= 1 if head has disability conditions†
Amman Govt	Binary	= 1 if HH lives in Amman Governorate
Syrian	Binary	= 1 if HH is Syrian
Size	Discrete	HH Size
Cash Eligibility	Binary	= 1 if HH is eligible to receive cash assistance from either WFP or UNHCR
WFP	Binary	= 1 if HH is enrolled in the World Food Program
Eviction Threats	Binary	= 1 if HH is currently under threat of eviction
Dep Assistance Ratio	Ratio	% of HH total income coming from assistance (UNHCR or WFP)
Dep Assistance Binary	Binary	= 1 if % of HH total income coming from assistance > Pooled Mean (= 0.568)
Rent Assistance	Binary	= 1 if HH has paid rent through assistance
SMEB	Continuous	HH Real Per Capita Monthly Survival Minimum Expenditure Basket (SMEB)†
INCOME	Continuous	HH Real Per-Capita Monthly Total Income†

Table A3
Correlations and descriptive statistics for $\hat{\rho}$ distributions. †: Estimated coefficient in OLS regression of $\hat{\rho}$ JOINT vs ($\hat{\rho}$ SMEB, $\hat{\rho}$ INCOME). Waves and Governorate dummies included. Robust standard errors clustered at Governorate level. Significance: *** = 0.01.

Panel (b)	Correlation between $\hat{\rho}$ distributions Lognormal			
Waves	2	3	4	Pooled
SMEB/INCOME	0.697	0.690	0.683	0.719
SMEB/JOINT	0.777	0.773	0.803	0.784
INCOME/JOINT	0.962	0.962	0.963	0.962
Beta SMEB†	–	–	–	0.474***
Beta INCOME†	–	–	–	0.507***
Panel (c)	**Descriptive statistics $\hat{\rho}$ SMEB (Lognormal)**			
Waves	2	3	4	Pooled
Min	0.071	0.076	0.297	0.071
Mean	0.541	0.526	0.498	0.522
Median	0.540	0.534	0.533	0.535
Max	0.707	0.707	0.707	0.707
Std Dev	0.063	0.062	0.061	0.062
Panel (d)	**Descriptive statistics $\hat{\rho}$ INCOME (Lognormal)**			
Waves	2	3	4	Pooled
Min	0.000	0.000	0.000	0.000
Mean	0.275	0.251	0.235	0.254
Median	0.203	0.205	0.181	0.197
Max	0.959	0.961	0.962	0.962
Std Dev	0.219	0.213	0.211	0.215
Panel (e)	**Descriptive statistics $\hat{\rho}$ JOINT (Lognormal)**			
Waves	2	3	4	Pooled
Min	0.032	0.071	0.102	0.032
Mean	0.407	0.304	0.243	0.318
Median	0.389	0.387	0.371	0.383
Max	0.718	0.715	0.718	0.718
Std Dev	0.136	0.134	0.136	0.135

Appendix B. Additional figures

See Figs. B1–B5.

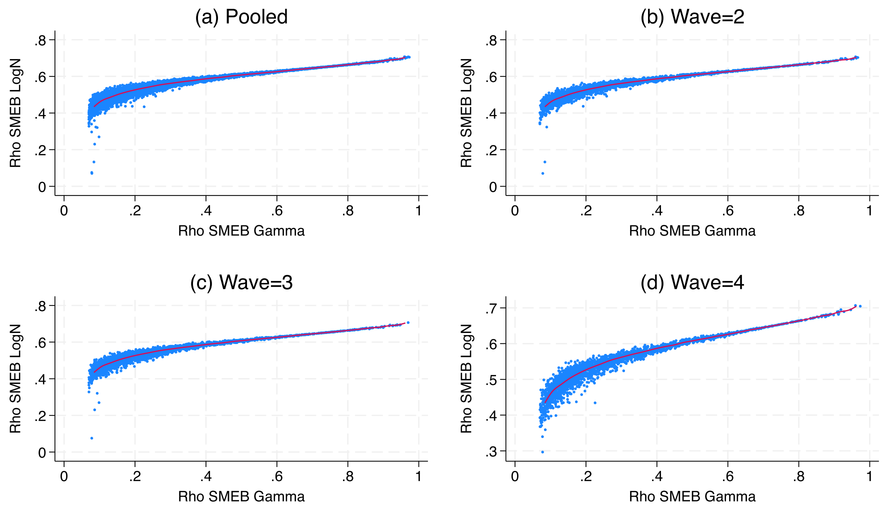

Fig. B1. Scatter plots of log-normal vs gamma for $\hat{\rho}$ SMEB across waves and in the pooled sample.

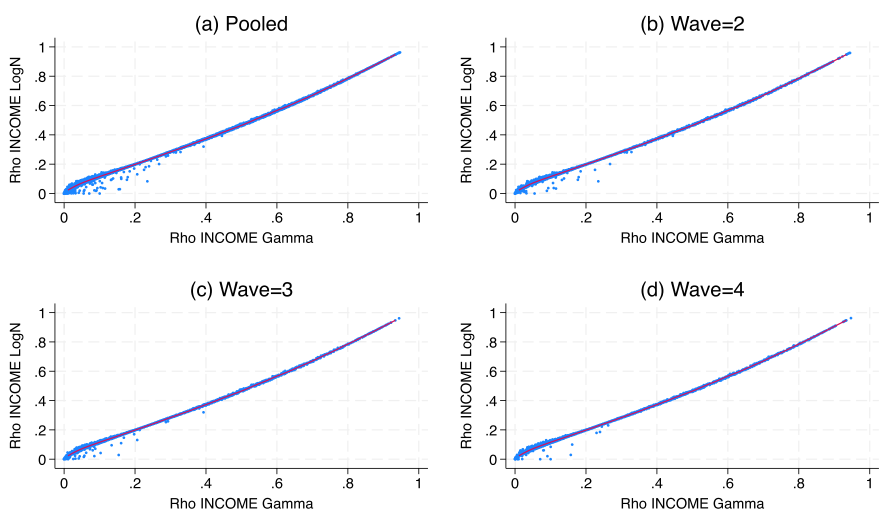

Fig. B2. Scatter plots of log-normal vs gamma for $\hat{\rho}$ INCOME across waves and in the pooled sample.

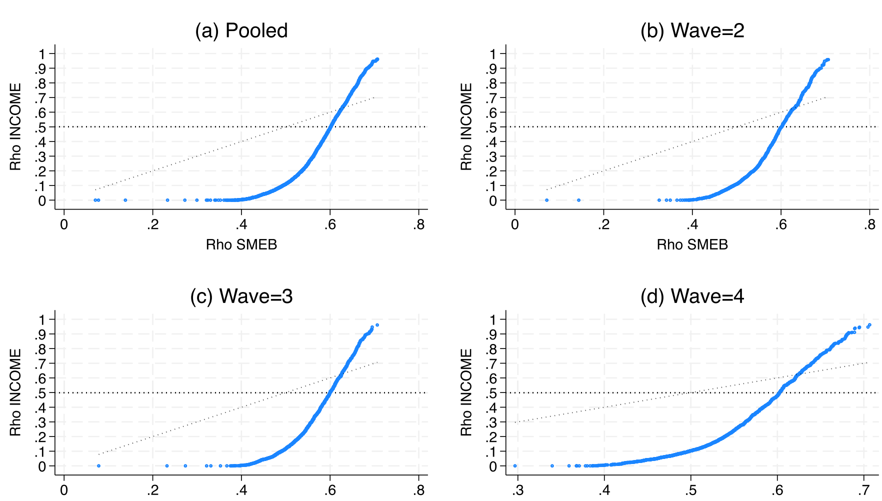

Fig. B3. Quantile-quantile plots of log-normal $\hat{\rho}$ SMEB vs $\hat{\rho}$ INCOME across waves and in the pooled sample.

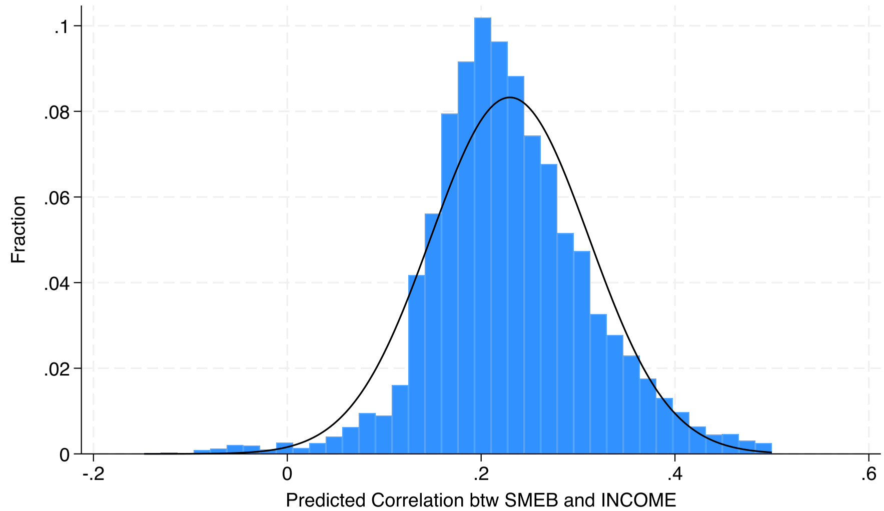

Fig. B4. Distribution of the predicted correlation between conditional SMEB and conditional INCOME in the pooled sample under the assumption of marginal log-normality. Solid line: Gaussian fit.

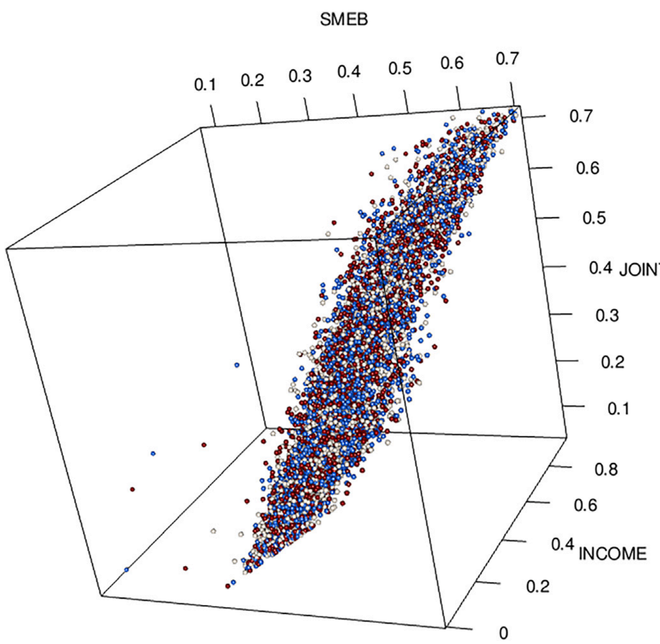

Fig. B5. 3D scatter plot of ($\hat{\rho}$ SMEB, $\hat{\rho}$ INCOME, $\hat{\rho}$ JOINT) across waves. Blue dots: Wave 2. Dark red dots: Wave 3. Yellow dots: Wave 4. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Data availability

We have shared the link to the dataset in the article.

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