Vulnerability Index of Migrant Construction Workers during Post Pandemic: An Investigative Study in West Bengal, India

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Abstract

The paper aims to investigate post pandemic vulnerability of migrant construction workers in West Bengal, India. This study assesses vulnerability of migrant workers in terms of coping capacity during and after disaster. Most of the research undertaken so far has focused on inherent vulnerabilities of migrant workers, however, coping capacity appraisal in the context of pandemic like disaster remains a challenge. The overall purpose is to measure composite vulnerability index and categorize it from low to high. The relative post pandemic vulnerability position of migrant construction workers is based on the magnitude of the index. The vulnerability index in terms of coping capacity has been calculated using multivariate statistical technique like Principal Component Analysis (PCA) where weights are assigned to each indicator using the first and second stage PCA. The sub-indices coping capacity (C), economic conditions after return (E) and re-migration and re-integration measures (R) have been computed using first stage PCA. Further, we have developed composite vulnerability indices for each (300 sample) workers using sub-indices as indicators applying second stage PCA. Results of sensitivity analysis suggest that sub-index R has sizeable positive loadings in both principal components 1 and 2 and this was used as an accurate indicator to determine vulnerability in its composite form. The practicality of this study exists in its capacity to address the sustainable reintegration issues as one of the major factors of coping capacity while dealing with disaster mitigation policies.

Key words: *Coping Capacity; Composite Vulnerability Index; PCA; Sustainable Reintegration; Sensitivity analysis*

1. Introduction

Internal migration is an important aspect in India's development trajectory and has a positive contribution on development of both sending and receiving areas (Deshingkar and Grimm, 2005). Lack of remunerative employment in native place and expectation of better livelihood led to seasonal/circular migration (Bhattacharya, 2020) within the country. Internal migrants are informally employed with low incomes, vulnerable to exploitation and are mostly engaged in '3D' jobs: dirty, dangerous and difficult. The integration of migrants in the destination state is often inhibited by the non-portability of the entitlement, cultural and ethnic discrimination and lack of coordination in social security networks between source and destination states. While there are problems of integration in the destination states, the disaster like COVID-19 pandemic had brought to the fore the vulnerabilities of migrant workers to cope with disasters.

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Vulnerability can be defined by the characteristics of a system that describe its potential to be harmed. While vulnerability cannot be directly observed or measured, composite vulnerability indices help us to quantitatively estimate relative vulnerability from selected indicators (Bucherie et al., 2022). A composite index is the most effective method for measuring the dynamic nature of vulnerability and these indices have influence on improved disaster risk reduction practices and adaptation planning to withstand the hazard impact. Various *composite vulnerability indices* have been developed till date for some specific contexts such as climate change, earthquake, flooding combined with hazard, exposure and coping capacity of socio-economic variables characterising the household and community vulnerability. Development of climate vulnerability index based on integrated vulnerability assessment (Pandey et al., 2017), quantifying coastal flood vulnerability (Wu, 2021), assessing urban vulnerability in the context of flood and heat hazard (Krellenberg and Welz, 2017), the computation of social vulnerability to floods in Huaihe River Basin (Zhang and You, 2014) have important contributions in vulnerability assessment and identifying vulnerable households. This indicator-based vulnerability assessment could help policy makers comparing the relative vulnerability of places known as spatial distribution of vulnerability. Scheur et al., (2011) conceptualize flood vulnerability by integrating economic, social and ecological dimension of risk and coping capacity in the city of Leipzig, Germany. Here the term risk is used to define starting point view of vulnerability and the term coping capacities (immediate hazard related response to disaster that can decrease vulnerability) is used in a way that could be called an end point view of vulnerability. This starting point-end point view approach helps to integrate different dimensions of risk and coping capacity that ultimately led to the identification of areas with low risk and low coping capacity, areas with low risk and high coping capacity, areas with high risk and low coping capacity and areas with high risk and high coping capacity. *Weighting criteria* is an essential part of the indicator-based multidimensional analysis of vulnerability. This weighting has a major influence on the final results of spatial vulnerability mapping. This indicator weighting can either be based either on the multivariate statistical method of Principal Component Analysis (PCA), used to reduce the research dimensions and generate weights for each indicator (Wu, 2021), or the most common approach used was the "equal weights" method. Multivariate statistical technique like PCA provides an alternative to the subjective determination of weights, as it presents an empirically objective approach to the selection of weights and circumvent the issue of multicollinearity (Jones and Andrey, 2007). Clark et al. (1998) and Cutter et al. (2003) used PCA to identify five components from 34 variables and eleven components from 42 variables respectively. The distribution of weights is the principal source of uncertainty in regard to vulnerability assessment. From an empirical point of view, PCA is preferred over Common Factor Analysis (CFA) as an indexing strategy because it is not necessary to make assumptions on the raw data, such as selecting the underlying number of common factors (Camara and Tuesta, 2014). Camera and Tuesta, also explained two-fold purpose of dividing the set of indicators into sub-indices. This will give additional disaggregated information as well as it also avoids weight biases toward indicators which exhibit highest correlation. While existing research on migrant workers tends to explore the existing vulnerabilities of migrant workers owing to lack of entitlements, inaccessibility to resources and social networking, adverse socio-economic and health conditions, but they lack the method to construct an *overall vulnerability index* within an integrative framework of multidimensional vulnerability assessment. Existing research on vulnerabilities was primarily focused on analysing potential factors that construct *"inherent vulnerabilities"* (Rajesh et al., 2014) including pre-disaster social, economic and institutional structure instead of coping capacities related to hazard-generic vulnerabilities. Given the gap in migrant vulnerability research and its assessment, specific to the context of hazard-induced disaster, the primary objective of this paper is to develop a comprehensive analysis of post pandemic vulnerability across internal migrant construction workers working in six regions of West Bengal, India. It emphasizes a specific kind of vulnerability reflected by adaptation of hazard and disaster response capacity during the process of disaster response or recovery (Shi et al., 2011). We discussed dimension reduction for determining significant factor loadings for the selected principal components using 1st stage PCA, rotated factor loadings of the indicators were analysed to interpret retained components on the basis of important indicators and finally overall vulnerability index was computed for each migrant construction worker by taking weighted average of all dimensional sub-indices using second stage PCA. This is a major *methodological advancement* in vulnerability assessment studies for identifying vulnerable migrant workers. Finally, the distribution of vulnerability index and computation of relative vulnerability using quartile-based categorization of vulnerability indices, have huge policy implication in various phases of institutional disaster risk reduction (Level et al.,2006) like preparedness, mitigation, rehabilitation and reintegration, during and after hazard impact. Crisis demands assessment of vulnerabilities of migrant workers during and after disaster and policies of return, reception and sustainable reintegration in the context of forced return during pandemic. This has a huge implication for decision making in disaster management and for adopting pre-disaster anticipatory action. The assessment presented here is intended to be a useful tool for local and national governments engaged in disaster risk reduction for internal migrant workers. The practicality of this study exists in its capacity to address the remigration and reintegration issues as one of the major factors of coping capacity for migrant construction workers exposed to disaster. The description of the study area, the conceptual framework and the methodology for computing composite vulnerability index is provided in the following sections.

2. Objective

The purpose of the study is to develop an index-based methodology approach for stratifying vulnerability profile of migrant construction workers in post-pandemic context. The main objectives are:

(a). To construct appropriate vulnerability index applying an objective weighting method based on PCA technique.

(b). To determine the contribution of each variable and contribution of each sub-indices to the overall index.

(c). To categorize the vulnerability profile of migrant workers and identifying migrant workers that are disproportionately affected by disaster.

(d) To identify sustainable coping strategy by assessing the migrant worker's perception while dealing with disaster mitigation policies.

3. Data and Methodology

3.1 Choice of Framework and Indicators

3.1.1 Choice of framework

With the aim of assessing migrant vulnerability quantitatively, a definition of the system of analysis (what is vulnerable?), the valued attributes of concern (why is it important?), the external hazard (to what is the system vulnerable?), and a temporal reference (when?) is required (Krellenberg and Welz, 2017; Fu¨ssel, 2007; El-Zein and Tonmoy, 2015). For reducing disaster risk, it is necessary to reduce vulnerability and exposure (Seddighi, 2020). In this paper, vulnerability has been conceptualised using end-point approach, which views vulnerability in terms of coping capacity of people and adaption to hazardous events and processes (Karagiorgos et al., 2016) instead of viewing vulnerability as an inherent property of a system prior to the occurrence of a hazard event which is known as starting-point approach (Žurovec et al., 2017). The interplay of institutions and hazard generic indicators has important contributions to assess and measure vulnerabilities and risks of coping capacity. Here the assessment framework was based on various phases of Institutional disaster risk reduction outlined by Level et al., 2006 (see Fig 1).

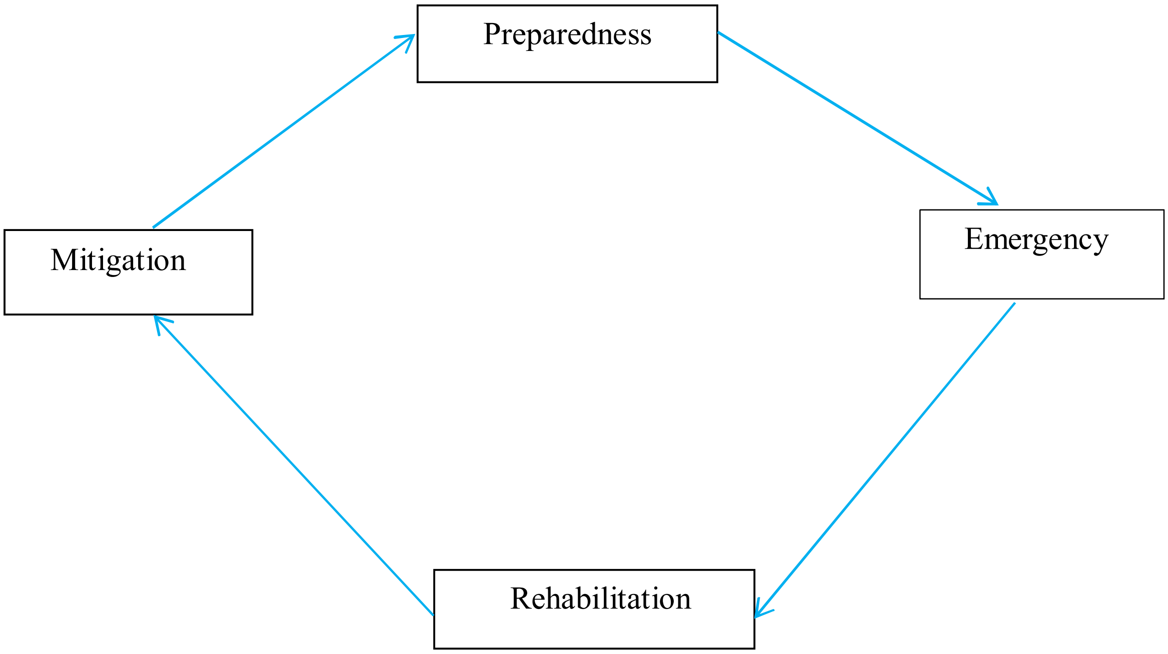

Figure1: Phases of institutional disaster risk reduction according to Lebel et al. (2006)

The domain economic condition after return (E) is under the institutional capacity of preparedness, the domain short term coping capacity (C) is under the institutional capacity of emergency and mitigation and domain reintegration and remigration (R) is under the institutional capacity of rehabilitation and reintegration. This could be referred to as disaster-immanent coping capacity and post-disaster coping capacity and allows assessing recovering abilities immediate and shortly after a disaster (Scheur et al.2011).

3.1.2. Choice of Indicators

A composite index provides the technical opportunity to monitor change, identify problems, contribute to priority-setting and policy formulation (von Schirnding, 2002). Our study views migrant workers working in the construction sector as a vulnerable system and hazard like pandemic as a stressor. The study identified nineteen state-specific vulnerability variables (in terms of effective disaster coping strategy) in post-pandemic context after conducting field surveys on the basis of migrant worker's perception and comprehensive literature review.

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Table 1: Indicators used for the three components of vulnerability. Source the authors

Component/Dimensions	Indicator	Rationale behind selection
1.Economic conditions after return	1. Job condition after return	Better economic position makes workers more resilient
	2. Income condition after return	
	3. Formal vocational training in the source region under PMKVY 3.0 after return	
	4. Opportunity for self-employment or starting own business	
	5. Accessibility to e-Shram Card / ASEEM Portal/Garib Kalyan Rozgar Abhiyan	
2. Short term preparedness / Coping Capacity	6. Ration under PMGKY	Level of protection measures given by government
	7. Direct benefit transfer under Jan-Dhan-Yojana	
	8. Provision of Work under MGNREGA	
	9. Benefits of Affordable Rental Housing Complexes for urban migrants under Pradhan Mantri Awas Yojana-Urban	
	10. Assistance for self-employment	
	11. Advance payment to farmers under PM-KISAN / Krishak Bandhu scheme of WB Govt.	
	12. Utilization of CESS (use of direct benefit transfer for CESS collected by State Welfare Board for Building and other Construction Workers)	
	13. Free LPG cooking gas cylinder to the beneficiaries of Pradhan Mantri Ujjwala Yojana for three months under PMGKY	
	14.Cash support of up to Rs.1000 by State (Under Sneher Parash scheme of W.B)	
3. Remigration and Reintegration measures	15. Experiencing stigmatization, Hostility and discrimination after return	Considered under the dimension of safe, orderly and regular migration of Migration Governance developed by IOM
	16. Facing crisis of mobility during return	
	17. Intention to remigrate	
	18. Reason behind remigration is the failure of returnees to secure employment in the origin	
	19. Long term reintegrative measures are preferred over short-term relief measures during pandemic	

Note: Here PMKVY is known as Pradhan Mantri Kaushal Vikas Yojana. ASEEM or Aatamanirbhar Skilled Employee Employer Mapping

3.2. Study Area

Primary data was collected through a field study and the field survey was done on a sample basis across three cities in West Bengal- Kolkata, Newtown and Salt Lake (under Greater Kolkata). Apart from selecting three urban agglomerations of the city of Kolkata in the Indian state of West Bengal- Kolkata, Newtown and Salt Lake, we have also collected primary data from Lalgarh which is a small town and gram panchayat in the Binpur1 CD block under the subdivision of the Jhargram district and city outside Kolkata like Ghatal which is a city and a municipality in Paschim Medinipur district. Data was also collected from migrant workers working in bridge construction over river Ajay connecting Kenduli in Birbhum and Shibpur in West Burdwan under Asansol, Highway division, Public Works (Roads) Directorate, West Bengal. A total of 300 migrant workers were selected for the survey by random sampling.
The city Kolkata was selected for highest concentration of interstate and intrastate migrant construction workers. New Town is an upcoming modern city (rapidly growing as a satellite city) which is one of the significant real estate destinations in the metropolis today. The region shows immense growth with a significant number of construction projects are currently underway. Salt Lake City is a planned satellite city and was developed to accommodate the burgeoning population of Kolkata. Lalgarh, a part of Jangalmahal-is now a mega construction site where infrastructure development is on at full pace and is now riding towards progress. The three areas-Ghatal (Paschim Medinipur), Lalgarh (Jhargram district) and West Burdwan were selected purposefully to capture the vulnerability of Adivasi and scheduled tribe migrant workers and the challenges faced by them during and after pandemic. This will help us to analyze vulnerability from the most disadvantaged sections of the society working as short term/seasonal migrants in rising construction industry of Paschim Medinipur, West Burdwan and Jhargram.

3.3. Questionnaire Design and scale development

We are interested in vulnerability measurement for ordinally scaled indicators, accordingly, responses have been arranged in a 5-point balanced scale ranging from 1=Extremely satisfied / strongly agree, 2=satisfied / agree, 3=neither satisfied nor dissatisfied / no opinion, 4=dissatisfied/disagree and 5=extremely dissatisfied / strongly disagree. In an ordinal scale, responses can be ranked or rated but the distance between responses is not measurable (Sullivan and Artino Jr, 2013).

3.4. Methodological Approach of Indicator-based Vulnerability Assessment

Data analysis includes the weighting and combining of selected indicators into composed indices (Krellenberg et al., 2014). But there is a disagreement over how to weight indicators and how values are aggregated. In our analysis, for each migrant worker, a composite vulnerability index was developed using objective methodology (unequal weighting) based on a set of state-specific indicators. There continues to be debate in the social sciences about whether principal component scores should be aggregated to create a composite index (Jones and Andrey, 2007).

3.4.1. Data Normalization

The values of the indicators were normalised in order to obtain comparable datasets and min-max normalises indicators to have an identical range [0, 1]. Min-Max normalisation could widen the range of indicators lying within a small interval, increasing the effect on the composite indicator more than the z-score transformation (Joint Research Centre-European Commission 2008).

3.4.2. Post-Pandemic Vulnerability Index using multivariate analysis PCA as an indexing strategy

PCA is commonly used to reduce the dimension of the data by transforming the variables that are most correlated into separate uncorrelated dimensions (Bucherie et al., 2022) preserving originality of data and the first component explaining most of the variance. The main merit of using PCA is that the choice of weights of the variables or sub-indices are auto assigned and endogenous to the system without any arbitrariness. First, we apply PCA to estimate three sub-indices (dimensions) representative of post pandemic vulnerability. Second, we apply PCA again to estimate the overall vulnerability index by using previous sub-indices as explanatory variables. The PCA method provides more empirically robust results than other approaches and a better understanding of the data variability (Ajtai et al., 2023). The different weights of the indicators provide a better understanding of the variables that influence vulnerability.

3.4.3. Covariance matrix computation

We compute covariance matrix (CM) in order to identify correlations between variables. Main diagonal of the matrix actually has variances of each variable. The entries of the covariance matrix are symmetric with respect to main diagonal as the covariance is commutative. Since the covariance matrix of a standardised dataset is merely the correlation matrix of the original dataset, a PCA on the standardised data is also known as a correlation matrix PCA (Jolliffe and Cadima,2016).

$$CM = \begin{bmatrix} cm_{11}\ cm_{12}\ \ldots cm_{1Q} \\ cm_{21}\ cm_{22}\ \ldots cm_{2Q} \\ \ldots \\ cm_{Q1}\ cm_{Q2}\ \ldots cm_{QQ} \end{bmatrix}$$

where the diagonal element cm_{ii} is the variance of x_i and cm_{ij} is the covariance of variables x_i and x_j. Here x_1, x_2…. x_Q are the indicators and there are Q observations. The weights for each principal component are given by the eigenvectors of the correlation matrix and the variance for each principal component is represented by the eigenvalue of the corresponding eigenvector (Krishnan, 2010).

3.4.4. Robustness analysis to run PCA

Table 2: Reliability statistics

Reliability Statistics	
Cronbach's Alpha	N of Items
.861	19

Cronbach Coefficient Alpha measures the internal consistency in the set of individual indicators, i.e., how well they describe a unidimensional construct. This coefficient explains reliability based on the correlation between individual indicators. Here Cronbach's alpha of 0.861 indicates high reliability of the data structure.

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Table 3: KMO and Bartlett's test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.888
Bartlett's Test of Sphericity	Approx. Chi-Square	1559.922
	df	171
	Sig.	.000

From the Kaiser-Meyer-Olkin measure of sampling adequacy, we obtained a value of 0.888. This shows adequacy of data to perform PCA analysis and can be ranked as *meritorious* as the value lies between 0.80-0.90 (Wu, 2021). The p-value for Bartlett's test of sphericity was less than 0.01, which is defined as suitable for PCA as the selected dataset is adequate. Therefore, several statistical tests like KMO and Bartlett's test of sphericity help us to assess appropriateness of using PCA.

3.4.5. Weighting and Aggregation

Here weights are calculated using the factor loadings of the indicators after rotation where loading (correlations) signifies how indicators are related to the principal components. Only those indicators which had loadings greater than 0.5 on the retained components were considered (Rajesh et al., 2018) and each component describes a unique dimension of migrant's vulnerability on the basis of selected indicators. Finally, object scores were computed for individual observation, which are numeric measurement of each migrant worker on each principal component and were combined to compute over all vulnerability index for each migrant worker surveyed.

For i=1…. n observation units, PCA transforms j=1…...p variables into m = 1…...p new uncorrelated variables (Z_1, Z_2…Z_P) called principal components where

$Z_{im}=c_{1m}x_{i1}+c_{2m}x_{i2}+\ldots\ldots\ldots+c_{Pm}x_{iP}$

where Z_{im} is the score for component m, x_{ij} is the values of standardised variables for observation i, c_{jm} is the weights (coefficients) that indicate how much each original variable j contributes to the linear combination forming this component (m). SPSS and EViews software were used to conduct the analysis of 1st and 2nd stage PCA.

3.5. Computation of Vulnerability Index

3.5.1. **Approach-1:** Computation of index (weighting and aggregation) using 1st stage PCA by picking all the indicators at the same time without estimating sub-indices

Communalities from the selected variables were extracted and are shown in supplementary material, Table S1. The communalities refer to the proportion of each variable's variance that can be explained by the principal components. The communality value of variable provisioning of free LPG cooking gas cylinder to the return migrant worker is just 0.353, which provide evidence of lower influence on the post pandemic vulnerability index as it is less well explained by the analysis.

Table 4: Eigen values of principal components

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.754	30.284	30.284	5.754	30.284	30.284
2	1.620	8.525	38.809	1.620	8.525	38.809
3	1.152	6.062	44.871	1.152	6.062	44.871
4	1.118	5.886	50.757	1.118	5.886	50.757
5	1.036	5.455	56.212	1.036	5.455	56.212

Note: Five components were extracted whose eigen values are greater than one

We reduce the number of dimensions by working with those principal components whose eigen value is greater than one, in order to avoid a higher degree of uncertainty in our results caused by significant dimension reduction just considering first principal component (Žurovec et.al, 2017). This criterion referred to as *Kaiser criterion* is a standard variable reduction method to use in PCA. The extracted five components out of 19 variables explained almost 57% of the variability of the data. *Varimax rotation* factor matrix is the key output of PCA and varimax is a variance maximizing strategy that helps to obtain a pattern of loadings on each component that is as diverse as possible. The varimax rotation reduces the number of individual indicators with high loading on one factor (Mavhura et al., 2017) and enhance the interpretability of the result. We have derived component scores for each migrant worker and these scores were combined to compute a post pandemic overall vulnerability index using equation: $VI_j = \sum F_i C_{ji}$ where VI_j represent vulnerability index for jth migrant worker. Fi represents the percentage of variance explained by component i, where i ranges from 1 to 5, where 5 is the total number of components resulting from extraction in PCA. Cji represents the object score/ component score coefficient of migrant worker j for component i. For example, weight for the first component was calculated by the following equation:

Eigen value of the first component E1 (% of variance)/E1+E2+E3……. +E5
where E1, E2…. E5 are the eigen value for the first factor, second factor….and fifth factor respectively. Therefore, weight = % of variance explained ÷ Total variance explained
Overall vulnerability index (VI) for each migrant worker is computed as follows:
VI = (Weight of first component) (Factor 1 score) + (Weight of second component) (Factor 2 score) +(Weight of third component) (Factor 3 score) + (Weight of fourth component) (Factor 4 score) +(Weight of fifth component) (Factor 5 score). In this case, we have picked all the indicators at the same time without computing dimension sub-indices, the methodology has some weight biases toward indicators which have highest correlation. In the following section we have computed vulnerability index using both first and second stage PCA to avoid weight biases.

3.5.2. **Approach-2:** Computation of Composite Index (weighting and aggregation) using both first and second stage PCA

In first stage PCA, we have computed dimension sub-indices and in second stage PCA we have computed overall post pandemic vulnerability index using dimensions as explanatory variables. In the first stage we estimate three intermediate vulnerability sub-indices as they contain highly correlated indicators within dimension (Camara and Tuesta, 2014). We have used second stage PCA on three sub-indices to compute their weights and they were aggregated to construct the overall vulnerability index. The computation of sub-indices (using first stage PCA) instead of estimating the overall index by taking all the indicators at the same time will help us –

- To get additional disaggregated information and to avoid weight biases toward indicators which exhibit highest correlation within dimension (Mishra, 2007).
- To provide a better understanding of the principal components that influence the vulnerability.
- To estimate the dimensions which can be useful information for policy makers and governments when designing post pandemic vulnerability strategies.

4. Results

4.1. *Outcomes of PCA without estimating sub-indices using method-1 and interpretation of retained principal components*

Table 5 provides a clear depiction of dimension reduction. Only five principal components were extracted from 19 variables (using approach-1). The results of the PCA indicate that the highest weight is assigned to the first principal component and this component is a reasonable representation of *reintegration issues with short term coping capacity.* Therefore, the first component is most important in explaining vulnerability. Within this dimension, highest weight was assigned to migrant's perception on *need of long term reintegrative measures over short term relief,* which can be explained by the fact that this indicator could have a direct impact on the resilience of this community and have an influence on adaptive capacity. This suggests policies related to *sustainable reintegration* should be mainstreamed in development planning.

Table 5: Rotated Component Loadings of the indicators (higher than 0.5) on selected principal components

Rotated Component Matrix[a]					
	Component				
	1	2	3	4	5
Long term reintegrative measures	.697				
Ration	.675				
Advance payment to farmers	.636				
Direct benefit transfer	.558				
Accessibility to eshram	.514				
Cess Utilization	.504				
Securing Employment in the origin		.751			
Intention to remigrate		.723			
Cash support		.666			
Self-employment opportunity		.540			
Training under PMKVY					
Affordable rental housing			.745		
Self-employment assistance			.648		
Free cooking gas					
Stigmatisation after return				.766	
Mobility crisis				.702	
MGNREGA					
Job condition after return					.832
Income condition after return					.804
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.					
a. Rotation converged in 6 iterations.					

4.2. The weighting result using method-2(estimating sub-indices and overall vulnerability index)

4.2.1. Economic conditions after return index

Table 6 displays the contribution of each indicator for the development of intermediate vulnerability *index-economic conditions after return*.

Table 6: Eigen vectors(loadings) for dimension: Economic conditions after return

Variable	PC 1	PC 2
Cumulative Variance	0.4704	0.6725
ACCESSIBILITY_TO_E_SHRAM_CARD__ASEEM_PORTAL_GARIB_KALYAN_ROZGAR	**0.43635**	**-0.56385**
FORMAL_VOCATIONAL_TRAINING_IN_THE_SOURCE_REGION_UNDER_PMKVY_3_0	0.468419	-0.48698
INCOME_CONDITION_AFTER_RETURN	0.44847	0.431277
JOB_CONDITION_AFTER_RETURN	0.446654	0.488006
OPPORTUNITY_FOR_SELF_EMPLOYMENT_OR_STARTING_OWN_BUSINESS	0.435382	0.144149

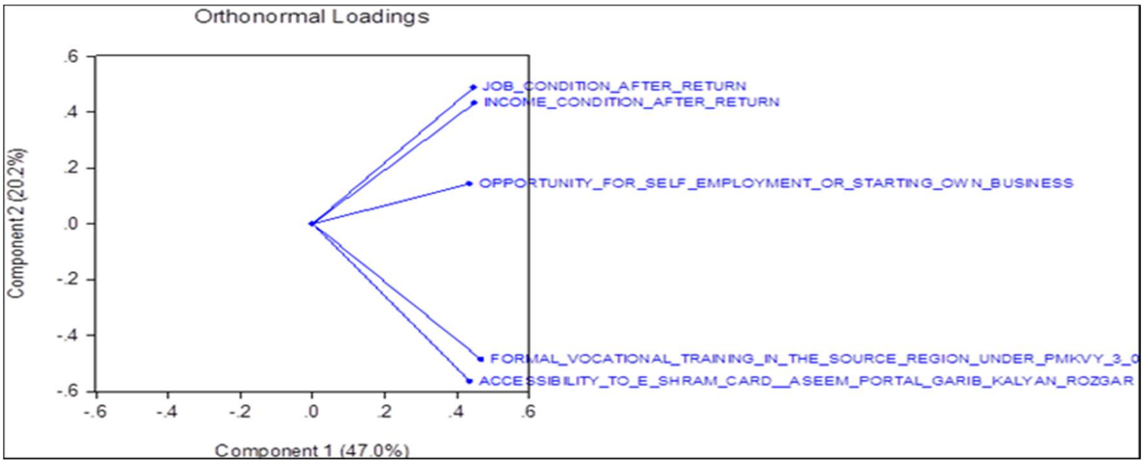

Figure 2: Orthonormal loading plot for variables under economic conditions after return

Sensitivity Analysis

From Table 6 and Fig 2 we observe that for the dimension, economic condition after return, first component which contains 47% of the total information in this dimension has an even contribution of the five indicators. The individual indicator that represents *accessibility to e-shram card/ASEEM portal/Garib Kalyan Rozgar* has sizeable loadings in both component 1 (positive loading) and component 2 (negative loading). In this context, this indicator may be represented as an *accurate indicator* to identify post pandemic vulnerability of migrant workers under the dimension economic conditions after return.

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4.2.2. Short term coping capacity index

Table 7 presents the contribution of each indicator for the development of intermediate vulnerability *index-short term coping capacity*.

Table 7: Eigen vectors(loadings) for dimension: Short term Coping Capacity

Variable	PC 1	PC 2
Cumulative Variance	0.3677	0.4819
ADVANCE_PAYMENT_TO_FARMERS_UNDER_PM_KISAN__RS_6000_PER_YEAR_IN_3	0.335247	-0.34747
ASSISTANCE_FOR_SELF_EMPLOYMENT	**0.331516**	**0.470802**
BENEFITS_OF_AFFORDABLE_RENTAL_HOUSING_COMPLEXES__ARHC_FOR_URBAN	0.306324	0.31226
CASH_SUPPORT_OF_UP_TO_RS_1000_BY_STATE__UNDER_SNEHER_PARASH	0.319936	0.376585
DIRECT_BENEFIT_TRANSFER_UNDER_JAN_DHAN_YOJONA_UNDER_PMGKY__IN_WB	0.378424	-0.39949
FREE_LPG_COOKING_GAS_CYLINDER_TO_THE_BENEFICIARIES_OF_PRADHAN_MA	0.322034	0.247371
PROVISION_OF_WORK_UNDER_MGNREGA	0.24577	-0.37472
RATION_UNDER_PMGKY__5KG_RICE_WHEAT___1KG_PULSES_EVEN_FOR_NON_CAR	0.393171	-0.23887
UTILIZATION_OF_CESS__USE_OF_DIRECT_BENEFIT_TRANSFER_FOR_CESS_COL	0.345856	0.00521

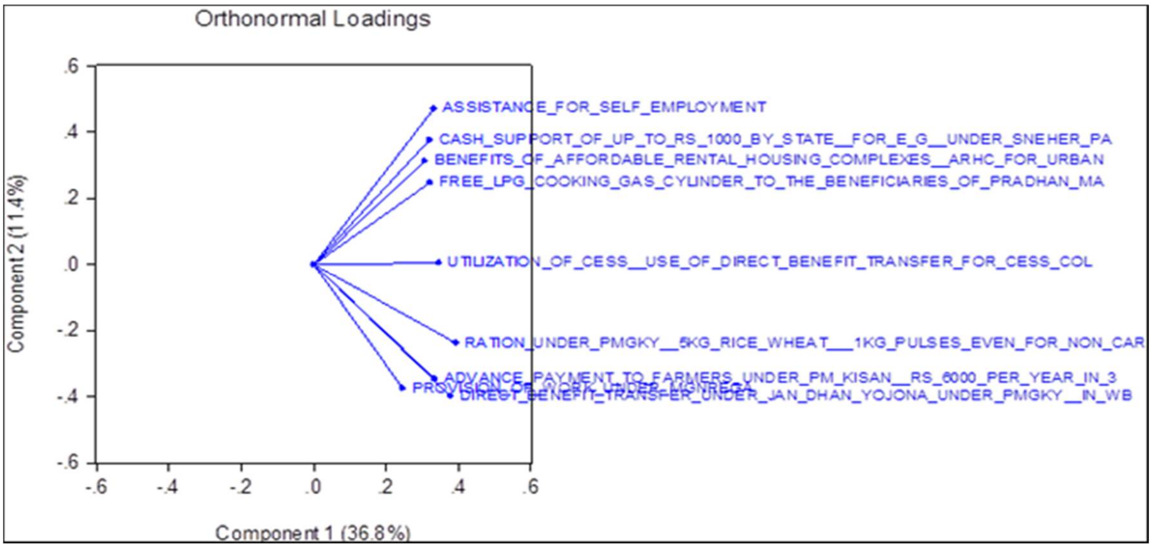

Figure 3: Orthonormal loading plot for variables under short term coping capacity

Sensitivity Analysis

From Table 7 and Fig 3 we observe that for the dimension, short term coping capacity, first component, accounts for almost 37% of the total information in this dimension, has an even contribution of the indicators except provision of work under MGNREGA. Although provision of work under MGNREGA contributes to the first component with low loading value, it has a higher negative loading in the second component. This indicates that this variable adds extra information but the structure is different from the first component. This shows that provision of work under MGNREGA has a broader issue beyond short term coping capacity and also related to policies like reintegration for returned migrants. *Assistance for self-employment* also adds extra information in the second component as it has the highest loading in second in addition to its contribution to the first component.

4.2.3. Remigration and reintegration index

Table 8 shows the contribution of each indicator for the development of intermediate vulnerability *index- Remigration and Reintegration issues*.

Table 8: Eigen vectors(loadings) for dimension: Remigration and Reintegration issues

Variable	PC 1	PC 2
Cumulative Variance	0.3291	0.5741
EXPERIENCING_STIGMATIZATION__HOSTILITY_AND_DISCRIMINATION_AFTER_RETURN	**0.355517**	**0.610392**
FACING_CRISIS_OF_MOBILITY_DURING_RETURN	0.396929	0.582707
INTENTION___TO_REMIGRATE	0.509473	-0.34651
LONG_TERM_REINTEGRATIVE_MEASURESS_ARE_PREFERED_OVER_SHORT_TERM	0.368263	-0.15418
RESEAON_BEHIND_REMIGRATION_IS_THE_FAILURE_OF_RETURNEES_TO_SECURE_EMPLOYMENT_IN_ORIGIN	0.566458	-0.37952

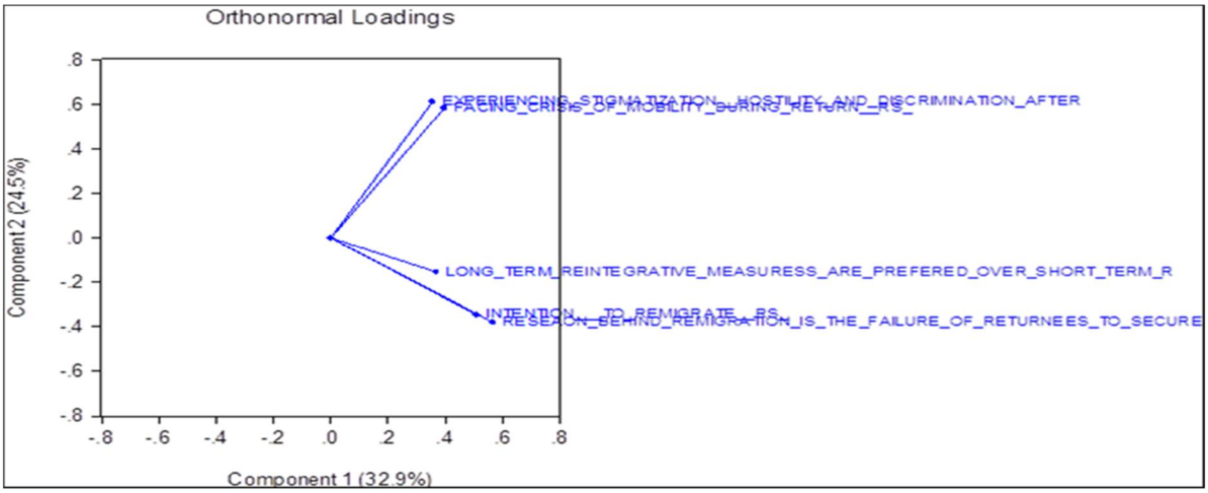

Figure 4. Orthonormal loading plot for variables under remigration and reintegration measures

Sensitivity analysis

Finally, for the remigration and reintegration dimension, we find (from Table 8 and fig 4) that five indicators contribute evenly to the first component, which accounts for almost 33% of the total information in the dimension. The indicator, *experiencing stigmatization, hostility and* *discrimination after return, has its highest weight* in the second component which might indicate that experiencing stigmatisation represents a stage of higher vulnerability and it has a huge implication in migrant workers' safe return and reintegration.

4.2.4. Estimating overall vulnerability index using second stage PCA

Table 9: Presenting the contribution of each sub-indices to the development of composite index

Variable	PC 1	PC 2
Cumulative Variance	0.7218	0.9211
SUB_INDEX_COPING_CAPACITY	0.616123	-0.293446
SUB_INDEX_ECONOMIC_CONDITION	0.601819	-0.423305
SUB_INDEX_REINTEGRATION	**0.508141**	**0.857148**

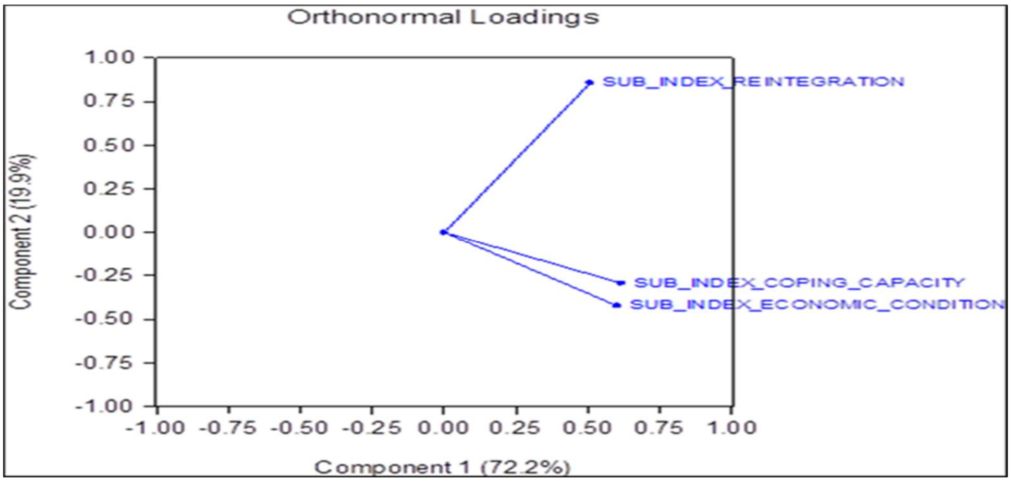

Figure 5. Orthonormal loading plot for sub-indices

Sensitivity analysis

In the second stage of PCA, from Table 9 and fig 5, the sensitivity analysis helps us to identify the factors that strongly contribute to output variability. In this case *sub-index for dimension remigration and reintegration has sizeable positive loadings* in both components 1 and 2 and this sub-index is used as an *accurate indicator* to determine vulnerability in its composite form.

4.3. Descriptive statistics of sub-indices and overall index V

Table 10 describes summary statistics of overall index and sub-indices.

Table 10: Descriptive statistics of sub-indices and overall index V

	Sub-Index C	Sub-Index E	Sub-Index R	Overall Index V
Count	300	300	300	300
Mean	1.400779	1.058044	0.759376	1.885000
Standard Deviation	0.416217	0.327118	0.240620	0.500176
Minimum	0.314086	0.255594	0.129439	0.600000
25% (1st quartile)	1.048137	0.797068	0.578388	1.500000
50% (median value)	1.503219	1.102560	0.764071	2.000000
75% (3rd quartile)	1.750644	1.346265	0.921257	2.300000
Maximum	2.145253	1.567318	1.344681	2.800000

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4.4. Stratification of vulnerability profile on the basis of the magnitude of overall vulnerability indices

Table 11: Stratification of vulnerability using PCA

Overall post pandemic vulnerability Index scores	Quartile Categories	Strata of Vulnerability	Number of migrants
0.600-1.500	1	Least Vulnerable	90
1.501-2.000	2	Lower Middle Vulnerable	65
2.001-2.300	3	Upper Middle Vulnerable	90
2.301 -2.800	4	Most Vulnerable	55

Table 11 presents stratification of vulnerability where scores of overall vulnerabilities were classified into four categories using quartile method of classification ranging from very low to very high values of vulnerability.

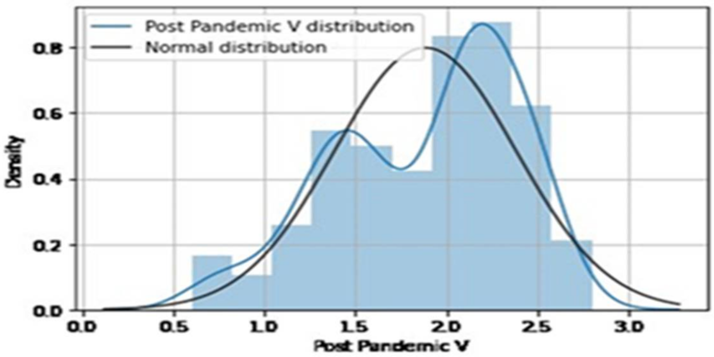

Figure 6: Distribution of overall vulnerability index V

Figure 6 presents the distribution of the migrant's vulnerability scores estimated by PCA method and its comparison with normal distribution.

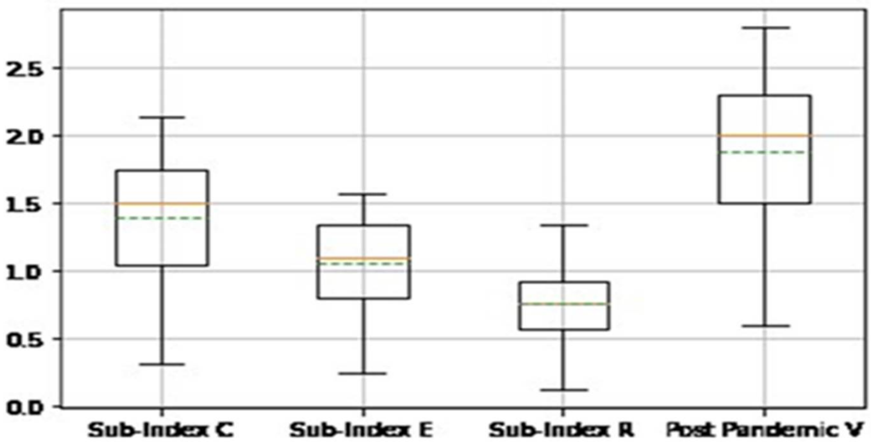

Figure 7: Box plot of sub-indices and overall index V

Figure 7 shows the box plot of sub-indices and overall index V. A box plot[34] is ideal for comparing distributions because the centre, spread and overall range are immediately apparent.

5. Discussion

5.1 Sensitivity analysis

The sensitivity analysis based on PCA method 1 shows highest weight was assigned to migrant's perception on *need of long term reintegrative measures over short term relief* under the dimension *reintegration issues with short term coping capacity.* Again, the sensitivity analysis based on PCA method 2 also suggests *sub-index for dimension remigration and reintegration* as an *accurate indicator* to determine vulnerability in its composite form. Therefore, in PCA-driven migrant vulnerability index *reintegration measures* are addressed as the most contributing to coping capacity. It can be concluded that migrant vulnerability in the context of disaster management is influenced more by *policies on sustainable reintegration* than economic conditions after return and short-term coping capacity and resilience of migrant community depends more on this factor.

5.2. Box plot analysis

Comparison of location of the median to compare averages of the data: If we compare the respective medians of each box plot of PCA method, then the median line of the box plot V lies outside the box of the boxplots of each dimension sub-indices. This shows that there is likely to be a difference between box plot of overall index V and boxplot of sub-indices. This shows that, on average, in PCA method, post pandemic vulnerability scores are higher than the vulnerability scores of sub-indices.

Comparison of dispersion: Dispersion measures the variability of a distribution which is measured by the interquartile range that is the length of each of the boxes of boxplot diagram. In PCA method, the interquartile range is highest for overall vulnerability index V which is 0.800 and lowest for sub-index R which is 0.343 (as shown by the lengths of the boxes), which means that dispersion of data is highest for vulnerability Index V and lowest for sub-index R. Overall range of the data set is also highest (2.213) for vulnerability index V and lowest (1.215) for sub-index R (as shown by the distances between the ends of the two whiskers for each boxplot). We can say that in PCA method, vulnerability *scores of overall index V* are *more scattered* than sub-indices C, E and R.

Comparison of skewness:

Descriptive statistics, such as skewness (a measure of symmetry), and kurtosis (a measure of 'peakedness') can be used to detect the type of distribution (Krishnan, 2010). Value of skewness estimated from the distribution of vulnerability score is -.513 and can be viewed as a *left skewed distribution* which is moderately skewed. The estimated value of kurtosis is -.639 which shows that the distribution is *platykurtic*. This kind of distribution is characterized by more values clustering towards the right side of the graph and there is a peak (mode) that is closer to the right side of the distribution, with a longer tail on the left side. This means there is *an inequality in the distribution* of vulnerability. In these two cases values of skewness and kurtosis are less than -1 and the distribution is not outside the range of normality. Sub-index R gives symmetric distribution as actual median line (orange) and the projected median line (doted green) coincide with each other and mean of the distribution is more or less equal to median. In PCA method,

[34] Box plot is a type of chart that depicts a group of numerical data through their quartiles. It makes comparing characteristics of data between categories very easy through the box and whisker markings' positions.

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the upper whisker for sub-index E is much shorter than sub-index C and vulnerability index V. This indicates that the data of sub-index E is slightly more negatively skewed than sub-index C and overall vulnerability index V.

General conclusions: Only distribution of vulnerability scores of sub-index R resembles with normal distribution and interquartile range is also lowest for sub-index R. This shows that distribution of vulnerability score under the dimension remigration and reintegration has lower variability, that is values in the data set are most consistent among all other sub-indices and overall index V. Knowing the properties of a normal distribution will help us calculate probabilities associated with sampling distributions, which is the key building block of inferential statistics.

6. Conclusions

This study was a first assessment of vulnerability of migrant construction workers in terms of coping capacity during and after disaster at the sub-national level in state West Bengal. Here we have developed multi-dimensional composite index within the framework of PCA that provides a better picture of vulnerability in terms of coping capacity and thereby stratification of migrant workers across different vulnerability profiles on the basis of quartiles. This index provides only a relative measure of vulnerability across migrant workers and it cannot provide information on absolute levels of vulnerability during and after disaster. We can rank migrant workers on the basis of the magnitude of the vulnerability scores using unequal weight (Table S1 under supplementary). The results of this study provided valuable knowledge about the current state of vulnerability in terms of coping capacity of migrant construction workers to disaster and the main determinants of vulnerability. This establish a baseline, which can be further updated, by computing vulnerability at different points of time as new indicators become available. The results show that the highest value of coping capacity was 2.1452 and lowest value was 0.3140 with the mean index score of 1.4007 and S.D of 0.4162. The highest index value of economic conditions after return was 1.5673 and lowest was 0.2555 with mean index score of 1.0580 and S.D of 0.327. The highest value of the index remigration and reintegration was 1.3446 and the lowest value was 0.1294 with mean index score of 0.7593 and S.D of 0.2406. Overall vulnerability index shows highest divergence of 2.2 with a mean index of 1.8850 and S.D of 0.50. Results indicated that, out of 300 migrant workers, 90 were categorized as least vulnerable, 65 as lower middle vulnerable, 90 as upper middle vulnerable and 55 as most vulnerable to pandemic like disaster. Local context specific indicators related to short term coping capacity and economic conditions after return were included in the analysis. In addition, inclusion of long-term reintegration and remigration measures, as mentioned in Migration Governance Framework of IOM (International Organisation for Migration), provided a more comprehensive assessment of the vulnerability and understanding of the issues like *sustainable reintegration* that needed to be further addressed. It was revealed from the box plot that distribution of sub-index R follows normal distribution with lowest variability. Based on the sensitivity results and box plot, it was concluded that, the dimension of remigration and reintegration (sub-index R) and the related indicators is the main determinant of vulnerability rather than the immediate coping capacity like economic conditions after return (sub-index E) and mitigation policies like short term coping capacity (sub-index C). This implies that remigration and reintegration measures in the source region play an important role in reducing vulnerability during and after disaster. In this context, the actions must be focused on Migration Governance Framework and Migration Governance Indicators (MGI) with special emphasis on crisis resilience and preparedness and active reintegration policy in the origin. Reintegration assistance can only be successful if there is some degree of reintegration in the economic, social and psychosocial dimensions after return.

When sustainable reintegration is achieved, return migrants can transform their future migration decisions into a matter of choice rather than necessity. These initiatives promote *good governance* of migration through collaboration with local and national authorities. In conclusion, our computation of vulnerability index shows adequate construct validity as we have used endogenous weighting in both the cases of sub-index formation and overall index formation (solely the product of statistical analysis) instead of subjective weighting and aggregation.

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.

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Table S1: Communalities

Communalities		
	Initial	Extraction
Job condition after return	1.000	.755
Income condition after return	1.000	.745
Training	1.000	.425
Self-employment opportunity	1.000	.608
Accessibility eshram	1.000	.541
Ration	1.000	.615
Direct benefit transfer under Jan Dhan Yojana	1.000	.561
MGNREGA	1.000	.413
Affordable rental housing	1.000	.576
Self-employment assistance	1.000	.606
Advance payment to farmers	1.000	.571
Cess Utilization	1.000	.476
Free LPG cooking gas availability	1.000	.353
Cash Support	1.000	.578
Stigmatisation after return	1.000	.613
Mobility crisis	1.000	.545
Intention to remigration	1.000	.545
Securing Employment in the origin	1.000	.627
Long term reintegrative measures	1.000	.530