Resilience and child malnutrition in Mali*

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Abstract

Despite increasing attention to resilience, the link between resilience and child malnutrition in Africa has so far never been empirically explored. Using detailed survey data from Mali, this paper examines whether the resilience capacity of households is a determinant of child malnutrition. After estimating the Resilience Capacity Index (RCI) by using a Structural Equation Model, an instrumental variable approach is followed. The impact of resilience capacity on child malnutrition is estimated by using the institutional presence of the state as an instrument for the RCI. Furthermore, the analysis captures differences in the relationship between resilience and the institutional presence of the state across regions. The empirical evidence presented here demonstrates that higher resilience capacity is in fact associated with both lower probability of having malnourished children and a lower number of malnourished children in the household.

Keywords: Resilience - Malnutrition - Structural equation model - Instrumental variable - Mali.
JEL classification codes: D12 - D80 - I12 - I32.

1 Introduction

Households living in Mali are exposed to numerous sources of external and internal shocks. In recent years, the rising prices of food and oil on international markets, the crisis in Libya and Cote d'Ivoire and a coup and internal strife in March 2012 significantly increased the population's exposure to shocks. The vulnerability of Malian households depends not only on their exposure to these shocks, but also on their resilience capacity. The latter is the capacity that ensures adverse stressors and shocks do not have long-lasting adverse development consequences. Therefore, household resilience refers to actions and strategies aiming ex ante to mitigate risks and ex post to cope with the shocks.

*The views expressed in this paper are those of the authors and do not necessarily represent FAO policy or the views of FAO.

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Despite the increasing attention to resilience, the link between household resilience and child malnutrition has not been addressed, especially in Africa. However, the interaction of poverty, food insecurity and crisis is recognized as a major factor in undernourishment in Africa (FAO 2012). The purpose of this paper is to empirically address the following question: does household resilience capacity affect child malnutrition? The interactions between resilience, on one side, and malnutrition, on the other, have never been empirically addressed, to the best of our knowledge.

The economic hypothesis has been tested using survey data from the Multiple Indicator Cluster Survey - Enquêete Légère Intégrée auprés des Ménages (MICS/ELIM), collected in Mali during 2009 and 2010. It has detailed information on household demographics, expenditure, child anthropometrics (which is useful for estimating measures of malnutrition: stunting, wasting and underweighting), health shocks and assets.

In order to measure household resilience, a two-step procedure using a latent variable model has been employed. First, resilience pillars (Access to Basic Services (ABS), Assets (AST), Sensitivity (S) and Adaptive Capacity (AC)) are estimated through Factor Analysis (FA) from observed variables. Second, a Structural Equation Model (SEM) is employed to predict a latent outcome, namely the Resilience Capacity Index (RCI), which identifies the relation between the incorporated pillars.

After estimating the RCI, an Instrumental Variable (IV) approach is employed in order to assess the effect of resilience on the probability of having malnourished children and on the number of malnourished children in the household. The source of identification in the two-stage least squares (TSLS) is the variation in the RCI that results from differences in the institutional presence of the state in the community where the household is located. Namely, this is calculated using the number of technical services provided by the state (per 100 inhabitants). The data was sourced from a commune survey implemented in Mali in 2008.

This paper is structured as follows: Section 2 conceptualizes resilience, then focuses on the link between resilience and malnutrition; Section 3 presents the data employed, and outlines the methodology used for estimating the RCI, then presents the final results and conclusions.

2 Materials and Methods

2.1 Resilience and Malnutrition - Conceptualizing Resilience

Resilience means different things to different people. Researchers, organizations and agencies have developed their own definitions of resilience and measurement methods. This paper follows the definition of resilience to food insecurity proposed by Alinovi et al. (2010a), namely, the capacity of a household to maintain a certain level of well-being in spite of shocks and stresses. Defining resilience as a capacity means that resilience is comprised of a set of ex ante attributes that should positively shift the likelihood function that describes the relationship between shocks and outcomes, such as food security (Barrett & Constas 2014; FSIN 2014). Based on this definition, the resilience framework seeks to assess the current strength of the food system and, hence, its ability to withstand shocks. Households are components of food systems and can themselves be conceived as both systems and sub-systems. Indeed, when a shock occurs, households are central decision-making units (encompassing consumption smoothing, assets selling, livelihood strategies choices and coping strategies adoption activities) and a point of interaction with institutions as well as with formal and informal social networks. For this reason, this paper considers the household to be the entry point for a resilience analysis.

Resilience is a multifaceted phenomenon that is not easily determined by one measurable dimension. Therefore, a common approach is to unpack resilience capacity by looking at (and measuring) each pillar that contributes to it. According to Pingali et al. (2005), resilience building strategies are based on the following principles: strengthening diversity, rebuilding local institutions and traditional support networks, reinforcing local knowledge, and building on household ability to adapt and reorganize. *Béné* et al. (2012) and *Béné* et al. (2015) see resilience as composed of three capacities: absorptive (e.g. coping strategies, risk management, savings groups), adaptive (e.g. use of assets, attitudes/motivation, livelihood diversification, human capital) and transformative (e.g. governance mechanisms, policies/regulations, infrastructure, community networks, formal safety nets). Other examples and proposed resilience structures can be found in Ellis (2000), Dercon (2002), DFID (2011), and Barrett & Constas (2014).

As in Di Tommaso (2007), we follow the selection criteria used in Robeyns (2003) to apply a list of appropriate pillars to the case of resilience capacity of Malian households. The pillars of resilience considered in this paper are: ABS, AST, S and AC.

Having ABS, such as schools, health centres, water and electricity, and, nearby markets, is a fundamental aspect of resilience for three main reasons. First, the capacity of generating income from assets, a key dimension of resilience, is constrained by access to market institutions, as well as non-market ones, public service provision and public policy (Dercon et al. 2008). For example, crop sales at the farm-gate or district market can result in very different revenues for farmer households. Furthermore, the density of the road network influences not only access to markets, but also the efficacy of aid distribution in response to disasters (Adger, et al. 2004). Recent evidence supports the association between access to basic services before a disaster and the rate of recovery after a disaster (Khan 2014). Second, ABS plays a key role in determining the risk exposure of households and communities. For example, "risk of illness is often closely related to particular environmental risks, linked to inadequate waste disposal, water supplies, and sanitation (Dercon, et al. 2008). These risks are also very relevant in urban areas (Moser 1998). Third, the relationships between state and civil society assume a relevant role in adaptation. Inefficient state institutions are likely to neglect adequate healthcare, housing and sanitation, leading to inefficient responses to shocks. In contrast, democracy and accountability push governments to manage risks and shocks adequately in order to be re-elected (Adger, et al. 2004).

Productive and non-productive AST are considered a relevant pillar of resilience as a preferable proxy for income.[1] When analysing household response to shocks, a central issue to be considered is the role of assets. When these contribute directly to the income generation process (as such, they are productive assets), shocks can have different consequences and lead to different behaviours. For instance, selling assets or slowing down asset accumulation could have important implications for future income generation. Transitory shocks can have long-term consequences when income loss leads to changes in asset investment decisions. Households might reduce their consumption to preserve their assets (asset smoothing) (Barrett & Carter 2005; Zimmerman & Carter 2003), or they can sell assets to protect consumption (consumption smoothing) (Hoddinott 2006).

AC represents household ability to adapt to the changing environment in which it operates. A household can become more adapted by improving its conditions in its own environment (Gallopín 2006). The adaptive capacity in social systems is strictly connected to the existence of institutions and networks that represent learning and store knowledge and experience, creating flexibility in problem-solving and balancing power among interest groups (Berkes et al. 2008). Having good adaptive capacity means being able to recuperate without significant reduction in crucial functions.

Resilience is seen as the capacity not only to absorb disturbances, but to reorganize while changes are taking place so as to retain the same functions, structures and feedback (Alinovi et al. 2008; Folke 2006; Walker et al. 2004). Therefore, the reorganizational capacity of a household is seen as fundamental in reacting to a shock and adapting to the new situation in order to return to a given level of well-being. In ecological systems, this capacity includes mechanisms for regeneration, such as seed production and spatial recolonization, whereas in the social sciences it entails relying on the intrinsic capacity of the household to find new solutions and generate new and sustainable livelihoods.

The capacity of adapting to perturbations and shocks is strictly connected with being able to learn from technological progress (Gallopín 2006). Usually, the higher the literacy rate, the higher the adaptive capacity. The least educated and lower-skilled members of a society are likely to be the most vulnerable to climate hazards in terms of livelihoods and geographical location.

Income diversification can also be considered an overarching strategy aimed at reducing risks and increasing options in the face of hazards (Turner et al. 2003). Indeed, if a household has many different income-generating activities, its capacity to withstand idiosyncratic or individual shocks is expected to be higher. Finally, demographic structure of the household affects adaptive capacity (Vincent 2007). For example, the lower the age-dependency ratio, the higher

[1] The data set used in this analysis does not include income information. Additionally, income is not easily calculated by using a household survey.

the adaptive capacity.

S relates to exposure to risk as well as to persistence or resistance to shocks. Risk exposure refers to the extent to which a household's livelihood is affected by a specific shock. Smith and Wandel (2006) argued that sensitivity is not separable from exposure. By expanding the definitions of persistence and resistance (Batabyal 2003), it is possible to define persistence as the amount of shock a system can absorb before becoming incapable of further reaction. A complementary definition is that of resistance, which is defined as how long it takes before the entire livelihood system of a household can be compromised by a shock. This aspect of sensitivity builds on the definition in Adger (2006): "the extent to which a human or natural system can absorb impacts without suffering long-term harm or other significant change. It is therefore important to assess the frequency and the intensity of shocks affecting a household over a given period of time.

2.2 Resilience and Malnutrition - Linking Resilience and Malnutrition

Malnutrition refers to any physiological condition caused by deficiencies, excess or imbalances in energy or nutrients necessary for a healthy and active life. In more detail, malnutrition encompasses overnutrition, undernutrition and micronutrient deficiencies.[2] Malnutrition is likely to contribute to more than one third of all child deaths, nevertheless the direct causal link between them is rarely recognized (WHO 2016). Inadequate breastfeeding, poor diets, severe and repeated infections, and the consumption of minimally nutritious or unsuitable foods can all contribute to malnutrition.

It is generally recognized that nutrition and resilience are strongly interlinked (Dufour et al. 2014; FAO 2014). The two phenomena are potentially codependent and mutually reinforcing. Specifically, nutrition is both an input to and an outcome of resilience. Indeed, malnutrition is thus both a health outcome as well as a risk factor for disease and mortality (Blössner and de Onis 2005).

On one side, well-nourished individuals are healthier and have greater physical reserves that ensure better outcomes in terms of productivity and earnings. Many empirical studies have shown that child malnutrition is associated with poorer cognitive achievement, as well as reduced earnings as an adult (Hoddinott 2006). Households with better earnings opportunities are expected to better manage the effects of shocks and stressors. Thus, households that are nutrition secure are better able to cope with shocks.

Nutrition is also highly correlated with singular pillars of resilience. For

[2] Overnutrition is a result of excessive food intake relative to dietary nutrient requirements. Undernutrition, too little food intake relative to nutrient requirements, can manifest in the form of acute malnutrition or wasting (low weight for height), chronic malnutrition or stunting (low height for age) and being underweight (low weight for age). Both overnutrition and undernutrition can be associated with micronutrient deficiencies (shortage of minerals or vitamins) (FAO 2014).

instance, households that are the least resilient and most affected by shocks face greater risk of malnutrition. The detrimental impact of climatic shocks on child nutrition is well-documented in the empirical literature (Maleta et al. 2003; Black et al. 2008). Bundervoet et al. (2009) also finds that exposure to civil war in rural Burundi has affected child malnutrition.

The connection between adaptive capacity and resilience is the most investigated in literature. Indeed, many empirical analyses confirm that parental, and especially maternal, education is a key factor influencing child malnutrition (Cochrane et al. 1982; Christiaensen & Alderman 2004).

In terms of basic services, the health sector is recognized as a key element in addressing the problem of child malnutrition (Quinn et al. 2005). While household income is recognized as one of the main drivers of malnutrition eradication (Sahn 1994), the role of assets has gained less attention within the empirical literature.

Nevertheless, in terms of focusing on specific components of resilience, the direct link between resilience capacity and child malnutrition has never been empirically investigated, to the best of our knowledge. The analysis proposed by the International Food Policy Research Institute (2016),[3] aimed at linking resilience and malnutrition, does not employ a resilience index, but two proxy variables of resilience; namely, the mother's level of education and the engagement in a non-agricultural job by the household head. The purpose of this paper is to estimate a resilience index, to capture the multidimensionality of resilience, and to test whether this capacity affects the level of malnutrition of children within the household unit. This involves the estimation of a resilience index and a procedure for testing its association with child malnutrition. After a description of the data used in the analysis, the procedure to estimate the RCI is described, followed by an outline of the empirical strategy aimed at linking resilience and malnutrition indicators.

3 Results and Discussion

3.1 Data

The analysis uses two surveys; one at the household level and one at the local level. The household survey is the MICS-ELIM.[4] It was implemented by Malian institutions from 2009 to 2010 the National Institute for Statistics, and the Ministry for Health, Social Development and Promotion of Family.[5]

[3]This reference is a forthcoming document that has not yet been published. The title of the document will be "Malnutrition and climate patterns in arid/semi-arid Kenya: a resilience analysis based on pseudo panel".

[4]The Mali MICS-ELIM surveys are part of the UNICEF program aimed at implementing household surveys to collect information on the situation of children and women. Additional information on the Mali MICS dataset can be found here: http://www.unicef.org/statistics/index_24302.html and on ELIM here: https://bamakobruce.files.wordpress.com/2012/01/rapport-elim-draft-juin-2011.pdf.

[5]Technical and financial support was provided by UNICEF, La Coopéeration Suédoise, UE, WB and USAID.

The sample of households used in the in this analysis consists of 8,660[6] observations and is representative at the national, regional, and urban/rural levels.

The variables used for estimating the pillars of resilience are the following:

- ABS includes distance (in minutes) from the nearest water source, whether the household has access to electricity or not, dummies for improved water, and toilet facilities
- AST takes into account both agricultural and non-agricultural assets and is composed of hectares of land owned by the household, Tropical Livestock Units (TLU), wealth index and house condition index
- AC results from the dependency ratio (number of dependent over active members), average years of education in the household, and dummy variables for economic activity (whether they are a wage earner, farmer, employer, independent or unemployed) of the household head
- S includes health shocks affecting children and women of the household. This pillar is composed of the number of children with diarrhoea, with malaria, and the number of infibulated women.

Table 1 reports the summary statistics of all the variables used for estimating the pillars of resilience.

Different malnutrition indicators based on anthropometric outcomes (weight and height) measured for all children aged 0-59 months in the MICS-ELIM survey have been used. As such (WHO 2006), the following have been specifically considered:

- stunting, a measure of chronic nutritional deficiency, based on a child's height and age[7]
- wasting, a measure of short-term nutritional deficiency, based on a child's weight and height[8]
- underweight, a composite measure of chronic and acute nutritional deficiency, based on a child's weight and age.[9]

[6] The initial sample consisted of 9,235. The definition of "household" adopted by the analysis is: all the people living in the same hut or home, related or not by blood lines (family) and sharing food, food expenses, income and other household assets for at least 6 of the 12 months preceding the interview. Therefore, the members of the household are defined on the basis of their usual place of residence. According to this definition, only those who are currently residents are considered household members. Thus the analysis excludes absent residents, visitors and members for whom information on their residence situation is missing. The latter are excluded since it is not possible to take into account whether they were present or not for at least six months. Furthermore, the analysis does not consider employees of the household as household members.

[7] A child is considered stunted if their Height-for-Age Z-score (HAZ) falls below 2 standard deviations below the normal height for their age-gender group.

[8] A child is considered wasted if their Weight-for-Height Z-score (WHZ) falls below 2 standard deviations below the normal weight for their age-gender group.

[9] A child is considered underweight if their Weight-for-Age Z-score (WAZ) falls below 2 standard deviations below the normal height for their age-gender group.

Table 1: Variables used for estimating the resilience pillars

Pillar	Variable	Mean	Std. Dev.	Min	Max
AST	Land owned (Ha)[a]	3.060	6.441	0	95
	Tropical Livestock Units[b]	0.433	0.952	0	10.857
	House condition index[c]	0.354	0.412	0	1.011
	Wealth index[d]	0.290	0.314	0	1.101
ABS	Improved water facility[e]	0.715	0.452	0	1
	Improved toilet facility[f]	0.383	0.486	0	1
	Electricity[g]	0.246	0.431	0	1
	Distance from water source[h](minutes)	11.763	20.848	0	360
AC	Dependency ratio[i](dependants/actives)	1.223	0.941	0	14
	Average years of education[l]	3.232	3.780	0	19
	HH head - wage earner[m]	0.154	0.361	0	1
	HH head - farmer	0.512	0.500	0	1
	HH head - employer	0.014	0.117	0	1
	HH head - independent or other	0.240	0.427	0	1
	HH head - no job	0.079	0.270	0	1
S	Children with diarrhoea[n]	0.303	0.645	0	7
	Children with malaria[o]	0.263	0.618	0	8
	Infibulated women[p]	1.873	1.905	0	21
	Observations	8,660			

[a] Land measures the hectares of agricultural land owned by the household.
[b] Tropical Livestock Units (TLU) standardizes different types of livestock into a single unit of measurement. The conversion factor adopted is: 1 camel; 0.5 cattle; 0.6 horses/donkeys/mules; 0.1 sheep/goats; 0.01 chickens; 0.2 pigs.
[c] House condition index is estimated using three dummies for having: (1) finished (parquet, vinyl or asphalt strips, ceramic tiles, cement, carpet) floor; (2) finished (metal, wood, calamine/cement fiber, ceramic tiles, cement, roofing shingles) roof; (3) finished (cement, stone with lime/cement, bricks, cement blocks, covered adobe, wood planks/shingles) walls.
[d] Wealth index is estimated using dummies for owning a TV, watch, fan, mobile, motorcycle, or fridge.
[e] Improved water facilities is a dummy equal to one if the household uses an improved water source (household connection, public standpipe, borehole, protected dug well, protected spring, rainwater collection) and zero otherwise.
[f] Improved toilet facilities is a dummy equal to one if the household uses improved facilities (connection to a public sewer, connection to a specific system, pour-flush latrine, simple pit latrine, ventilated improved pit latrine) and zero otherwise.
[g] Electricity is a dummy equal to one if the household has access to electricity and zero otherwise.
[h] Distance from water source expresses how many minutes the household spends to go to the nearest water source, get water and come back. It is equal to zero if the household has a water source in its dwelling or yard/plot.
[i] Dependency ratio is the share of dependent (younger than 15 and older than 64 years old) members of the household over the active (of age between 15 and 64 years) members.
[l] Average years of education measures the average years of education of household members.
[m] Household (HH) head - wage earner, farmer, employer, independent or other and no job are all dummies for economic activity of the household head.
[n] Children with diarrhoea is the number of children with diarrhoea in the household in the past two weeks.
[o] Children with malaria is the number of children with malaria in the past two weeks.
[p] Infibulated women is the number of infibulated women present in the household.

Since resilience is expressed at the household level, the same level of aggregation for child malnutrition has been adopted. Therefore, three dummies have been created for having at least one stunted child, one wasted child and one underweight child. In the sample used in the analysis, 31 percent of the households have at least one stunted child, 24 percent have at least one wasted child and only 14 percent have at least one underweight child (see Table 5 in the Appendix). Furthermore, continuous variables expressing the number of stunted, wasted and underweight children have also been used.

Additionally, a survey at the commune level (the third level of administrative units observed in Mali, after region and district) has been also employed. The sample size of this survey is 703, corresponding to the number of Malian communes. This survey was implemented in 2008 by the Observatoire du Developpement Humain Durable et de la Lutte Contre la Pauvrete (ODHD/LCP).[10] The survey contains detailed information on infrastructures, education, health, cultural activities, religion and governance.

3.2 Estimating the Resilience Capacity Index

Resilience is an unobservable and multidimensional construct. As expressed above, resilience capacity is made up of sub-components. However, different approaches for measuring resilience have been developed in recent years; they can be broadly divided into those that aggregate and those that do not aggregate the pillars of resilience (Constas et al. 2016).[11] The approach followed here aggregates resilience indicators through SEMs.

In this paper, resilience is conceived as composed of four pillars. Specifically, the equation followed is:

$$RCI_{h,t} = f(ABS_{h,t} + AST_{h,t} + AC_{h,t} + S_{h,t} + \epsilon_{h,t}) \quad (1)$$

where the RCI at time t is a function of the four pillars of resilience mentioned above.

There are advantages of using an index to represent a complex multidimensional construct. An index, or composite measure, allows for more concise description of the overall resilience capacity. It may facilitate comparability, ranking, targeting and aggregation across settings. An index is easily incorporated into other modelling procedures. It might be noted here that the idea of constructing indices in measurement is, however, viewed by some as too reductionist; there is a concern that details that are important for understanding resilience may be lost or hidden in a measurement approach that relies on an index. The information (e.g. items/elements of a household survey) on which an index is based may indeed be useful for an intricate analysis of interventions and policy components. The existence and use of an index does not, however,

[10]Additional information on data collection by ODHD/LCP can be found here: http://www.odhd-mali.org.

[11]This reference is a forthcoming paper in the FSIN Technical Series. The authors of this reference are Constas M, d'Errico M., Garbero, A, and the title of the paper will be "Quantitative Analyses for Resilience Measurement".

prevent one from examining the relative importance and empirical contribution of the contents of an index.

There are typically three possibilities when it comes to the aggregation phase of a multidimensional index: (i) the Multidimensional Poverty Index (MPI) (Alkire and Foster 2009), which aggregates various dimensions of poverty by pre-assigning a weight to each of them; (ii) multivariate statistical techniques, such as latent variable approaches, and data reduction techniques, like Principal Component Analysis (PCA), Factor Analysis (FA), Structural Equation Models (SEM) and Multiple Indicator and Multiple Causes (MIMIC); or (iii) moment-based approaches. In this paper, the multivariate statistical technique is adopted, considering that both the moment-based approach and the MPI approach do not allow for the evaluation of the relevance and role of each pillar, and of each variable within each pillar. Different algorithms can be chosen to aggregate the underlying variables into a single index (Krishnakumar & Nagar 2008).

PCA is a data reduction technique that can be employed to reduce the dimensionality of a data set by finding a new set of variables called principal components that are uncorrelated, retain most of the sample information, and are ordered by the fraction of the total information that each component explains. PCA can also be used to reduce the number of variables that enter a regression analysis, by isolating the most relevant ones. However, it cannot be employed to create a latent variable that is linearly correlated with the underlying dimensions, as PCA does not consider linear relations during the estimation process.

In addition, PCA is computed without assuming any underlying structure in the data; components are calculated using the variance of the observable variables, and the total variance appears in the solution (Costello & Osborne 2005). The method takes into consideration not only the variance of the variable that can be attributed to the latent factor, but also that part of the variance which is uniquely attributable to the variable itself (the so-called uniqueness).

In many practical applications, binary (dummy) or categorical variables have been chosen as the underlying variables to enter the PCA. The literature has widely recognized the inadequacy of the method when using categorical variables. For example, this is the case in Kolenikov and Angeles (2004). One of the limitations lies in the calculation of the correct covariance matrix, given that dummies have very low variance and do not guarantee a valid covariance matrix. Correlation analysis is only appropriate for examining the relationship between meaningful quantifiable data.

FA allows instead for the reduction a set of observed variables used as proxy indicators for the latent variable, as a single variable, the component of interest. The data reduction mechanism relies on finding cross-correlations between the observed variables, identifying the number of (unobservable) factors reflected in the correlations, and predicting the latent outcome as a linear combination of underlying factors. If all the variables defining the latent variable are closely correlated, they may be represented by a single factor. When variables cluster into a few groups of closely related variables, they can be represented by more than one factor. The number of factors should be chosen so that at least 90 percent of the total variability is explained.

SEMs allow for the measurement of covariates among observed variables and correlations among dimensions (Acock 2013; Bollen et al. 2007). SEM combines factor analysis with regression. It is assumed that the set of measured variables is an imperfect measure of the latent variable of interest. SEMs use a factor analysis-type model to measure the latent variable via observed variables, while simultaneously using a regression-type model to identify relationships among the underlying variables (Bollen 1989). Generally, the estimation methods developed for SEMs are limited to the normally distributed observed variables, but in most cases (including this one), many variables are nominal or ordinal. The literature has proposed some attempts to broaden SEMs to include nominal/ordinal variables, but there are difficulties regarding computational aspects (Muthén 1984). It is also possible to use generalized latent variable models (Bartholomew & Knott 1999; Skrondal & Rabe-Hesketh 2004) to model different response types. A major concern in using SEMs for measuring resilience is that the algorithms of SEM procedures are usually totally data driven.

It is important to stress that, contrary to SEMs, FA assumes that the residual errors (i.e. unique factors) are uncorrelated with each other and with the common (i.e. latent) variable. These assumptions rarely hold in reality, particularly in a framework where resilience is indexed to an outcome such as food insecurity or well-being. In these instances, the probability of intra-dimension correlation is high. Therefore, SEMs tend to be the preferred estimation frameworks as they include correlation among residual errors and allow for a number of goodness of fit tests. Although SEMs require a greater computational effort compared with factor analysis, they allow for model calibration until a satisfactory level of goodness of fit is achieved.

The RCI is estimated through a two-step procedure by using a latent variable model. Despite the differences among papers, the approach of modelling household resilience as a latent variable[12] is very widespread in the related literature (Alinovi et al. 2010a and 2010b; Tefera & Kayitakire 2014; Ciani & Romano 2014; Browne et al. 2015).

In the first step, the pillars of resilience are estimated through FA (Scott 1966) from observed variables. The procedure allows for the reduction of the set of variables used as proxy indicators for the latent variable, as a single variable, the pillar of interest.

After estimating the four pillars from observed variables, SEM is employed to predict a latent outcome, namely the RCI, which identifies the relationship between the incorporated pillars. In the estimation of the RCI, the probability of intra-pillar correlation is high. Therefore, SEM is the preferred estimation approach.

The fit indices in Table 2 indicate a good model fit.

[12] Alternative methods to multivariate statistics for estimating resilience are moment-based approaches (Barrett & Constas 2014; Cissé & Barrett 2015) and the use of non-aggregative measures (Maxwell et al. 2013).

Table 2: SEM results

Pillars	
ABS	1
	(0)
AST	1.012***
	(0.0149)
S	0.0725***
	(0.0135)
AC	0.685***
	(0.0125)
Observations	8,660
Chi2	91.72
P value	0.000
RMSEA	0.102
Pr RMSEA	0.000
CFI	0.992
TLI	0.949

*** p<0.01, ** p<0.05, * p<0.1.
Standard errors in parentheses.

The RCI estimated above provides a general idea of the resilience attribution in the whole country. As shown in Figure 1, the northern areas which extend into the Sahara and the Sahel are the least resilient, while the southern regions host most of the country's economic activities and are the most resilient. Unsurprisingly, the capital, Bamako (the darkest spot in the bottom left side of the map, labelled "9"), is the most resilient area of the country.

3.3 Identification strategy

To identify the association between the RCI and child malnutrition, a two-stage least square regressions (2SLS) was adopted:

$$M_{h,t} = \beta RCI_{h,t} + \gamma X_{h,t} + \delta D_{h,t} + \epsilon_{h,t} \tag{2}$$

where subscript h denotes the household and t the time. $RCI_{h,t}$ is the independent variable of interest, estimated as described in the previous section. $X_{h,t}$ is a vector of household characteristics including household size, squared value of household size, age of household head, and gender of household head (summary statistics of all controls are shown in Table 5 of Appendix). Controlling for all the variables used for estimating the RCI was specifically avoided. $D_{h,t}$ are regional dummies[13] and $e_{h,t}$ is the usual error term. $M_{h,t}$ represents different dependent variables for child malnutrition at household level, namely (i) three continuous variables expressing the number of stunted, wasted and underweight children in the household and (ii) three dummies for having at least

[13] The Bamako region is entirely urban. By using it as reference category in the empirical model, this also controls for whether the household lives in an urban or rural area.

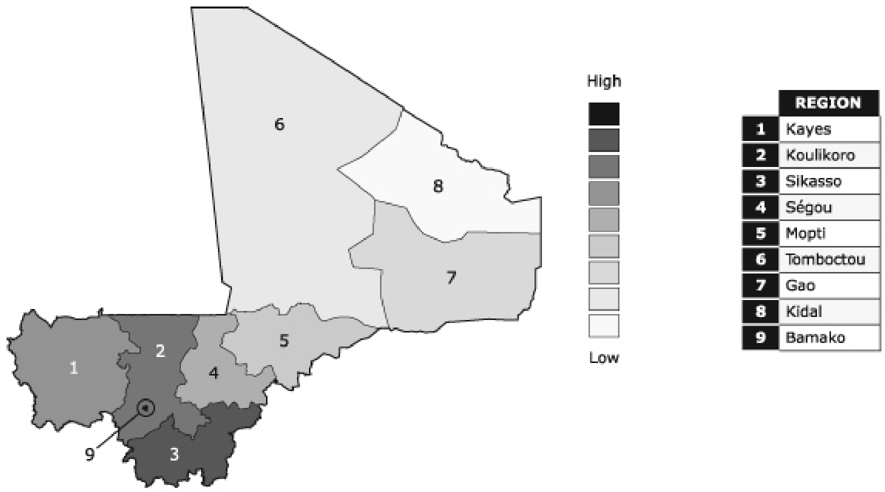

Figure 1: Resilience capacity map in Mali (2009/10)

one stunted, wasted or underweight child. Consequently (2) has been estimated by using six different outcome variables.

There are several reasons why resilience might be endogenous. First, there is reverse causality as malnutrition might affect resilience. Children's poor health might also affect family resilience, if additional resources have to be spent on child care. Second, there may be omitted factors that affect both resilience, on one hand, and child malnutrition, on the other. Some examples of aspects of resilience that may go unobserved include the general skills and abilities of a household, or the formal and informal networks that a household might be connected with and on which it relies in the case of special needs. Third, there may be a measurement error of resilience capacity itself.

Endogeneity arises when, for instance, the RCI is jointly determined with the outcome of interest or is correlated with the error term. Therefore, the assumption of no covariance existing between one of the variables of the model and the error term is violated:

$$Cov(X_i, \epsilon_i) \neq 0 \tag{3}$$

In (3), one of the regressors is correlated with the error term of the estimated model. The presence of endogeneity will bias the estimation of the parameters of interest. There are different ways to deal with endogeneity, depending on the source of the endogeneity (omitted variable bias, reverse causality and measurement error). For instance, an analysis of correlated missing regressors or instrumental variable approaches are potential solutions.

The fundamental assumption for consistency of least square estimators is that the model error is unrelated to the regressors (i.e. $E\ (u|x)=0$). In case this assumption fails, the ordinary least square estimator is inconsistent and it can no longer be given a causal interpretation (Cameron & Trivedi 2009). When there is the concern of endogeneity that may bias the estimates of the impact, an Instrumental Variable (IV) estimator is adopted. The IV estimator provides a consistent estimator under the (strong) assumption of the existence of a valid instrument z (i.e. variables that are correlated with the regressors x and satisfy $E\ (u|z)=0$). The IV estimation technique originated in research on simultaneous equation models by Wright (1928) and Reiersøl (1941). A good framework for casual inference can be found in Angrist & Krueger (2001). Therefore, to assert that β is an estimate of the causal effect of resilience on malnutrition outcomes, the number of technical services of the state (per 100 inhabitants) in the community where the household lives for the period *t-1* has been used for the first-stage regression:

$$RCI_{h,t} = \alpha TS_{c,t-1} + \gamma X_{h,t} + \delta D_{h,t} + \epsilon_{h,t} \tag{4}$$

Since both continuous and binary outcome variables have been considered, both the 2SLS and IV Probit models have been adopted.

3.4 Final results

Before looking at the main results of the models, the goodness of the instrument needs to be evaluated. The RCI has been applied using the number of technical services of the state (per 100 inhabitants) in the community. This instrument serves as a proxy for the institutional environment of the community where the household is located, which is an important determinant of household resilience. Indeed, institutions are recognized as one of the essential characteristics that help to form a resilient system by allowing access and entitlement to assets that enhance resilience (IFAD 2015). This instrument is in line with the view of Angrist & Krueger (2001), according to which a good instrumental variable comes from detailed knowledge of the economic mechanism and institutions determining the regressor of interest.

A good instrument needs to be strong and valid. First, it must be a strong predictor of the RCI. Second, the exclusion restriction must be verified; namely that the institutional presence of the state does not directly affect child malnutrition.

In terms of relevance, first-stage regression (Table 6, column 1, in Appendix) suggests a positive and statistically significant association between the presence of the state in the community and the resilience capacity of its inhabitants. Since the RCI lacks a scale, the focus is on the direction of the link only and not on the magnitude of the effect. The instrument also passes the weak identification test, as suggested by the Angrist-Prischke F statistic that is well above the commonly used reference value of 10 (see Table 4).

Additionally, in terms of exogeneity, the instrumental variable at *t-1* has been used in order to avoid a potential contemporaneous effect on outcome variables.

It has also been avoided to use the integer number of technical services of the state instead of its ratio per 100 inhabitants, in order to control for the density of inhabitants of each community.

Table 3 reports the results of probit in columns 1 for stunting, 4 for wasting and 7 for underweight; of IV Probit in column 2 for stunting, 5 wasting and 8 underweight. For each measure of malnutrition, the first column is used as benchmark, while columns 2, 5 and 8 show the main results. Table 4 has the same format for presenting the Ordinary Least Squares (OLS) and 2SLS effect of the RCI on the number of malnourished children of the household.

In columns 1, 4 and 7 of Table 3, the probit estimates suggest a negative and statistically significant correlation between the resilience capacity and the likelihood of having malnourished children. However, reverse causality, omitted variable bias or measurement error may bias the results. Columns 2, 5 and 8 of the same table display the results of the IV Probit model, instrumented with the number of technical services of the state (per 100 inhabitants). These also confirm the negative and statistically significant association between resilience and the probability of having malnourished children. Although the magnitude of the effect cannot be investigated, interestingly, the bigger impact of RCI is on the probability of having stunted children. This, as an individual measure of malnutrition, is one that indicates chronic malnutrition. In other words, the association of resilience is stronger with this long-term outcome.

To improve the efficiency of the estimates and control for region-related trends in malnutrition, the interaction terms between the number of technical services of the state in the commune and regional dummies are added in both specifications (IV Probit and 2SLS). Indeed, the instruments excluded from the resilience regression are the variables for the technical services of the state, which relate to eight regional dummies. Because the regional dummies are also included in the second-stage equations, the interactions capture differences in the relationship between resilience and the institutional presence of the state across regions. The rationale for adding these interaction terms is the increase in precision. It allows for the fact that the relationship between resilience and institutional presence of the state may change across regions. This specification allows for controlling for unobservable factors that explain why the households choose to reside in a specific region, which is linked with the household's RCI and child malnutrition. This may create a bias in our results. In the Appendix, Column 2 of Table 6 presents the results of the resilience equation with the inclusion of all the interaction terms as instrumental variables. The second-stage results when all the interactions are used as IVs are shown in columns 3, 6 and 9 of Table 3, respectively for stunting, wasting and underweight for the probability of having malnourished children. In in columns 3, 6 and 9 of Table 4, these are for the number of malnourished children that are present in the household. The negative association between resilience and child malnutrition is confirmed when this set of IVs is included in the specifications. The magnitude of the RCI effect only slightly decreases with respect to the use of only one instrumental variable.

Table 3: Probit and IV Probit models of having malnourished children

	Stunting			Wasting			Underweight		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probit	IVProbit	IVProbit	Probit	IVProbit	IVProbit	Probit	IVProbit	IVProbit
RCI	-0.367***	-0.868***	-0.720***	-0.284***	-0.817***	-0.663***	-0.140***	-0.785***	-0.565***
	(0.0216)	(0.137)	(0.108)	(0.0224)	(0.144)	(0.111)	(0.024)	(0.147)	(0.124)
HH size	0.137***	0.125***	0.131***	0.118***	0.107***	0.113***	0.0975***	0.0843***	0.0925***
	(0.00493)	(0.00887)	(0.00599)	(0.00493)	(0.00845)	(0.00584)	(0.00521)	(0.00852)	(0.00601)
Sq. HH size	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.00010)	(0.00013)	(0.00011)	(0.00010)	(0.00013)	(0.00011)	(0.00010)	(0.00012)	(0.00011)
Age HH head	-0.008***	-0.010***	-0.0097***	-0.008***	-0.010***	-0.0096***	-0.007***	-0.010***	-0.009***
	(0.00110)	(0.00120)	(0.00120)	(0.00120)	(0.00120)	(0.00120)	(0.00130)	(0.00130)	(0.00140)
Male HH head	0.0339	0.00794	0.0173	0.110*	0.0747	0.0881	0.152**	0.101	0.124*
	(0.05380)	(0.05180)	(0.05280)	(0.05830)	(0.05630)	(0.05710)	(0.06800)	(0.06350)	(0.06600)
Kayes[a]	-0.248***	-0.925***	-0.722***	-0.380***	-1.076***	-0.880***	-0.176**	-1.021***	-0.736***
	(0.07040)	(0.20200)	(0.16100)	(0.07580)	(0.19900)	(0.16200)	(0.08150)	(0.20500)	(0.17800)
Koulikoro	-0.0844	-0.774***	-0.564***	-0.153**	-0.871***	-0.661***	-0.0318	-0.896***	-0.599***
	(0.06990)	(0.21000)	(0.16400)	(0.07380)	(0.21100)	(0.16600)	(0.07930)	(0.21400)	(0.18200)
Sikasso	0.141**	-0.547**	-0.330**	0.161**	-0.566**	-0.344**	0.0299	-0.814***	-0.520***
	(0.06610)	(0.21500)	(0.16300)	(0.06880)	(0.22200)	(0.16800)	(0.07590)	(0.21100)	(0.17700)
Segou	0.057	-0.675***	-0.447***	0.124*	-0.653***	-0.417**	0.0512	-0.861***	-0.542***
	(0.06900)	(0.22600)	(0.17300)	(0.07180)	(0.23500)	(0.17800)	(0.07910)	(0.22800)	(0.19000)
Mopti	-0.0554	-0.849***	-0.603***	-0.0189	-0.857***	-0.604***	0.0356	-0.964***	-0.613***
	(0.07020)	(0.24000)	(0.18400)	(0.07400)	(0.24800)	(0.18900)	(0.08090)	(0.24700)	(0.20500)
Tomboctou	0.0889	-0.768***	-0.500**	0.316***	-0.610**	-0.324	0.250***	-0.846***	-0.455**
	(0.07450)	(0.26400)	(0.2000)	(0.07680)	(0.28300)	(0.21000)	(0.08500)	(0.27800)	(0.22600)
Gao	-0.0283	-0.852***	-0.601***	0.119	-0.762***	-0.498**	0.0348	-0.998***	-0.643***
	(0.07710)	(0.25200)	(0.19500)	(0.08020)	(0.26600)	(0.20300)	(0.09060)	(0.25700)	(0.21800)
Kidal	-0.213**	-1.201***	-0.897***	-0.134	-1.179***	-0.865***	0.0327	-1.228***	-0.786***
	(0.08570)	(0.29500)	(0.22800)	(0.09070)	(0.30600)	(0.23400)	(0.09920)	(0.31100)	(0.25800)
Constant	-1.244***	-0.328	-0.639***	-1.458***	-0.466	-0.798***	-1.737***	-0.487	-0.985***
	(0.08550)	(0.31600)	(0.22400)	(0.09100)	(0.34100)	(0.23700)	(0.10200)	(0.37600)	(0.27100)
Observations	8,548	8,548	8,548	8,548	8,548	8,548	8,548	8,548	8,548
Pseudo R-squared	0.194			0.169			0.119		
Wald test		8.96	9.00		9.21	9.73		11.82	9.95
p-value		0.0028	0.0027		0.0024	0.0018		0.0006	0.0016

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

[a] The excluded regional dummy is Bamako.

Table 4: OLS and 2SLS models of number of malnourished children

	Stunting			Wasting			Underweight		
	(1) OLS	(2) 2SLS	(3) 2SLS	(4) OLS	(5) 2SLS	(6) 2SLS	(7) OLS	(8) 2SLS	(9) 2SLS
RCI	-0.178***	-0.392***	-0.313***	-0.101***	-0.322***	-0.253***	-0.031***	-0.211***	-0.129***
	(0.0101)	(0.1040)	(0.0651)	(0.0084)	(0.0877)	(0.0544)	(0.0058)	(0.0618)	(0.0377)
HH size	0.0541***	0.0545***	0.0544***	0.039***	0.039***	0.0394***	0.022***	0.022***	0.0228***
	(0.0024)	(0.0025)	(0.0025)	(0.0020)	(0.0021)	(0.0021)	(0.0014)	(0.0015)	(0.0014)
Sq. HH size	0.0003***	0.0002***	0.0003***	0.00006	0.00006	0.00006	-0.00003	-0.00003	-0.00003
	(0.00005)	(0.00005)	(0.00005)	(0.00004)	(0.00005)	(0.00004)	(0.00003)	(0.00003)	(0.00003)
Age of HH head	-0.0031***	-0.004***	-0.0039***	-0.002***	-0.003***	-0.0035***	-0.001***	-0.002***	-0.0021***
	(0.0005)	(0.0008)	(0.0007)	(0.0004)	(0.0006)	(0.0006)	(0.0003)	(0.0004)	(0.0004)
Male HH head	0.0126	0.0033	0.0067	0.0289	0.0196	0.0226	0.0148	0.0071	0.0106
	(0.0257)	(0.0268)	(0.0261)	(0.0214)	(0.0225)	(0.0218)	(0.0148)	(0.0158)	(0.0151)
Kayes[a]	-0.175***	-0.455***	-0.352***	-0.157***	-0.438***	-0.348***	-0.0430**	-0.279***	-0.171***
	(0.0337)	(0.1400)	(0.0908)	(0.0280)	(0.1180)	(0.0759)	(0.0194)	(0.0831)	(0.0526)
Koulikoro	(0.0111)	-0.289**	-0.186**	(0.0455)	-0.324***	-0.235***	(0.0085)	-0.242***	-0.135***
	(0.0333)	(0.1390)	(0.0900)	(0.0277)	(0.1170)	(0.0752)	(0.0192)	(0.0823)	(0.0521)
Sikasso	0.159***	(0.1100)	(0.0111)	0.0841***	-0.186*	(0.0994)	0.0181	-0.209***	-0.105**
	(0.0321)	(0.1350)	(0.0872)	(0.0266)	(0.1130)	(0.0729)	(0.0185)	(0.0799)	(0.0505)
Segou	0.0158	-0.274*	-0.167*	0.0538*	-0.237*	-0.144*	0.0157	-0.228***	-0.117**
	(0.0336)	(0.1450)	(0.0936)	(0.0279)	(0.1220)	(0.0782)	(0.0193)	(0.0859)	(0.0542)
Mopti	(0.0539)	-0.373**	-0.255**	(0.0105)	-0.330**	-0.228***	0.0215	-0.247***	-0.124**
	(0.0338)	(0.1590)	(0.1020)	(0.0280)	(0.1330)	(0.0850)	(0.0194)	(0.0939)	(0.0589)
Tombouctou	0.0075	-0.332**	-0.207*	0.104***	-0.236*	(0.1260)	0.0620***	-0.223**	(0.0929)
	(0.0366)	(0.1690)	(0.1080)	(0.0304)	(0.1420)	(0.0906)	(0.0210)	(0.0999)	(0.0627)
Gao	(0.0405)	-0.370**	-0.249**	0.0204	-0.310**	-0.204**	0.0054	-0.272***	-0.145**
	(0.0381)	(0.1650)	(0.1060)	(0.0316)	(0.1380)	(0.0888)	(0.0219)	(0.0975)	(0.0615)
Kidal	-0.127***	-0.527***	-0.380***	-0.0711**	-0.473***	-0.344***	0.0042	-0.332***	-0.179**
	(0.0409)	(0.1990)	(0.1270)	(0.0340)	(0.1670)	(0.1060)	(0.0235)	(0.1180)	(0.0736)
Constant	0.0937**	0.413**	0.295***	0.0645*	0.385***	0.282***	0.0221	0.291***	0.168***
	(0.0411)	(0.1610)	(0.1050)	(0.0341)	(0.1350)	(0.0874)	(0.0237)	(0.0951)	(0.0605)
Observations	8,548	8,548	8,548	8,548	8,548	8,548	8,548	8,548	8,548
R-squared	0.358	0.324	0.344	0.250	0.192	0.223	0.136	0.039	0.108
Angrist-Pischke test		84.75	23.843		84.75	23.843		84.75	23.843
Sargan test			10.168			13.664			9.139
p-value			0.2535			0.091			0.3307

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

[a] The excluded regional dummy is Bamako.

The same negative relationship between the RCI and child malnutrition is confirmed when the numbers of stunted, wasted and underweight children, respectively, have been used as a dependent variable (see Table 4) in all specifications.

The results of both IV Probit and 2SLS are robust in the use of the number of technical services divided by the household size, and in their interaction with regional dummies as instrumental variables to control for any size effect. The results of the second-stage are presented in Table 7 of the Appendix.

4 Conclusions

This paper examined whether households' resilience capacity affects child malnutrition in Mali. After estimating the RCI, the index has been instrumented with a proxy of the institutional environment in the community where the household lives.

There is strong evidence that household expenditure and child nutritional outcomes are affected by household resilience capacity. The results suggest that household resilience is negatively associated with the probability of having malnourished children, as well as with the number of malnourished children in the household.

Significant policy implications can be drawn from this analysis. In particular, any policy affecting the resilience capacity of households may have positive, indirect effects on child malnutrition.

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Appendix

Table 5: Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Resilience Capacity Index (RCI)	0.000	0.968	-2.624	2.707
Stunting (dummy)	0.306	0.461	0	1
Wasting (dummy)	0.236	0.425	0	1
Underweight (dummy)	0.143	0.350	0	1
Stunting (number)	0.469	0.912	0	13
Wasting (number)	0.328	0.701	0	8
Underweight (number)	0.170	0.453	0	4
N. of technical service of the State (per 100 in.)	0.032	0.034	0	0.229
Number of technical service of the State (per 100 in.) pc	0.007	0.013	0	0.183
HH size	9.163	8.064	1	80
Squared HH size	148.982	361.300	1	6400
Age of HH head	49.359	15.078	17	95
Male HH head	0.888	0.315	0	1
Kayes	0.112	0.316	0	1
Koulikoro	0.117	0.321	0	1
Sikasso	0.136	0.342	0	1
Segou	0.116	0.320	0	1
Mopti	0.120	0.325	0	1
Tomboctou	0.091	0.287	0	1
Gao	0.077	0.266	0	1
Kidal	0.068	0.251	0	1
Bamako	0.165	0.371	0	1
Observations[a]	8,548			

[a] The sample of the analysis is reduced to 8,548 households due to the presence of missing values on the number of technical services of the State by commune.

Table 6: First-stage: Instrumenting regression results for Resilience Capacity Index

	(1)	(2)
	RCI	RCI
Tech. services of the State (per 100 in.)	3.102***	19.59**
	(0.33700)	(07.66000)
HH size	0.00175	0.00212
	(0.00259)	(0.00257)
Squared HH size	0.00002	0.00001
	(0.00006)	(0.00005)
Age of HH head	-0.00560***	-0.00534***
	(0.00061)	(0.00060)
Male HH head	-0.0411	-0.0405
	(0.02740)	(0.02720)
Kayes[a]	-1.382***	-1.081***
	(0.03400)	(0.05760)
Koulikoro	-1.381***	-1.412***
	(0.03390)	(0.05580)
Sikasso	-1.340***	-1.381***
	(0.03260)	(0.06340)
Segou	-1.432***	-1.434***
	(0.03370)	(0.06130)
Mopti	-1.568***	-1.415***
	(0.03330)	(0.05230)
Tomboctou	-1.702***	-1.627***
	(0.03730)	(0.06160)
Gao	-1.632***	-1.813***
	(0.03830)	(0.06570)
Kidal	-2.193***	-2.067***
	(0.05210)	(0.08320)
Tech. services of the State (per 100 in.) * Kayes		-24.81***
		(7.730)
Tech. services of the State (per 100 in.) * Koulikoro		-13.14*
		(7.723)
Tech. services of the State (per 100 in.) * Sikasso		-12.74
		(7.803)
Tech. services of the State (per 100 in.) * Segou		-13.87*
		(7.768)
Tech. services of the State (per 100 in.) * Mopti		-19.24**
		(7.698)
Tech. services of the State (per 100 in.) * Tomboctou		-16.51**
		(7.720)
Tech. services of the State (per 100 in.) * Gao		-8.907
		(7.782)
Tech. services of the State (per 100 in.) * Kidal		-16.96**
		(7.685)
Constant	1.474***	1.386***
	(0.04090)	(0.0536)
Observations	8,548	8,548
R-squared	0.351	0.361
Adjusted R-squared	0.35	0.359

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

[a] The excluded regional dummy is Bamako.

Table 7: Instrumenting Resilience Capacity Index with the number of technical services pc: second stage results

	(1)	(2)	(3)	(4)	(5)	(6)
	Stunting	Wasting	Underweight	Stunting	Wasting	Underweight
RCI	-1.255***	-1.210***	-1.187***	-0.466***	-0.344***	-0.144***
	(0.04430)	(0.05030)	(0.04820)	(0.08410)	(0.06980)	(0.04730)
HH size	0.0833***	0.0726***	0.0535***	0.0546***	0.0396***	0.0228***
	(0.01110)	(0.00980)	(0.00853)	(0.00254)	(0.00211)	(0.00143)
Squared HH size	-0.0009***	-0.0008***	-0.00055***	0.00025***	0.00006	-0.00003
	(0.00014)	(0.00013)	(0.00011)	(0.00005)	(0.00005)	(0.00004)
Age of HH head	-0.0104***	-0.0102***	-0.00951***	-0.00474***	-0.00398***	-0.00215***
	(0.00095)	(0.00096)	(0.00097)	(0.00076)	(0.00063)	(0.00043)
Male HH head	-0.0198	0.0222	0.0308	0.000116	0.0187	0.00995
	(0.04270)	(0.04560)	(0.04740)	(0.02710)	(0.02250)	(0.01530)
Kayes[a]	-1.520***	-1.593***	-1.559***	-0.553***	-0.467***	-0.191***
	(0.09110)	(0.08400)	(0.08260)	(0.11500)	(0.09530)	(0.06460)
Koulikoro	-1.445***	-1.489***	-1.519***	-0.386***	-0.353***	-0.156**
	(0.10200)	(0.09860)	(0.09190)	(0.11400)	(0.09440)	(0.06400)
Sikasso	-1.270***	-1.271***	-1.445***	-0.204*	-0.214**	-0.125**
	(0.11300)	(0.11600)	(0.09190)	(0.11000)	(0.09160)	(0.06200)
Segou	-1.415***	-1.383***	-1.531***	-0.376***	-0.267***	-0.138**
	(0.11500)	(0.12000)	(0.09840)	(0.11900)	(0.09830)	(0.06660)
Mopti	-1.603***	-1.587***	-1.664***	-0.484***	-0.363***	-0.147**
	(0.11500)	(0.11800)	(0.10400)	(0.12900)	(0.10700)	(0.07270)
Tomboctou	-1.627***	-1.511***	-1.699***	-0.450***	-0.270**	-0.117
	(0.13200)	(0.15000)	(0.12800)	(0.13800)	(0.11400)	(0.07740)
Gao	-1.661***	-1.581***	-1.747***	-0.485***	-0.344***	-0.169**
	(0.12300)	(0.13300)	(0.11000)	(0.13500)	(0.11200)	(0.07570)
Kidal	-2.122***	-2.080***	-2.132***	-0.667***	-0.514***	-0.208**
	(0.13500)	(0.14000)	(0.13100)	(0.16200)	(0.13400)	(0.09100)
Constant	0.831***	0.720***	0.812***	0.524***	0.418***	0.191***
	(0.21200)	(0.22900)	(0.23500)	(0.13200)	(0.10900)	(0.07410)
Observations	8,548	8,548	8,548	8,548	8,548	8,548
R-squared				0.296	0.18	0.098
Wald test	28.14	46.42	48.45			
p-value	0.000	0.000	0.000			
Angrist-Pischke test				15.169	15.169	15.169
Sargan test				19.724	19.129	9.244
p-value				0.011	0.014	0.322

*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

[a] The excluded regional dummy is Bamako.