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Proximity to markets, resilience, and food security: A cross-country empirical analysis*

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Abstract

Scholars advocate that proximity to final markets increases food security, but empirical evidence is scarce. We shed light on this issue by applying a hybrid empirical approach – which combines machine learning algorithms, vulnerability models and mediation analysis – to a new cross-country household dataset made available by the International Fund for Agricultural Development in 2017-2018. Specifically, we find positive and statistically significant associations among proximity to markets, resilience and food security. We tested the plausibility of the exclusion restriction that market proximity does not affect food security fluctuations other than through its impact on resilience capacity by implementing an instrumental variable approach and a mediation analysis. The latter method reveals that market proximity accounts for a significant share of the positive correlation between household resilience and food security outcomes. The dampening role played by market proximity in decreasing welfare fluctuations is also confirmed when replacing food security outcomes with income ones. Overall, these findings suggest that policymakers should prioritize interventions to improve infrastructure and access to markets as a means to boost household resilience and, in turn, decrease welfare fluctuations and vulnerability to food insecurity.

Keywords: rural development, market chain, vulnerability, resilience, food security

JEL-Codes: Q12; O12; C31, C3

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1. Introduction

One of the leading forces behind today's economic development in low-income countries is crop commercialization. Agricultural commercialization enhances efficiency and gains from trade, leading to economic growth and welfare improvement. Furthermore, the integration of smallholder farmers into traditional markets is supposed to have strongly pro-poor outcomes, thanks to a virtuous cycle of efficiency, which increases household income, consumption, food security and nutritional outcomes (Montalbano et al., 2018). Nevertheless, participation in the market chain may be less beneficial to the food security levels of the poorest and most vulnerable groups, who are often unable to catch any of the gains from increased market orientation (Bouis & Haddad, 1990; von Braun et al., 1991; Abbi et al., 1991; Kennedy & Cogill, 1987; Popkin, 1980).

Indeed, facing up to market forces, especially global linkages, makes farmers vulnerable for specific reasons, such as risk-aversion to price changes and bargaining power (Bellemare et al., 2013). Yet factors like market power, marketing costs and asymmetric information limit efficient spatial and vertical price transmission to farmers (Meyer & Cramon-Taubadel, 2004). Several agriculture markets are oligopsonistic, with a large number of farmers and very small numbers of processors and private and/or public traders. Furthermore, the geographic dispersion of smallholder farmers allows traders to exploit their market power, having a significant impact on market structure and reducing farmers' welfare (Sexton, 2013; Swinnen & Vandeplas, 2012; Swinnen & Vandeplas, 2014; Kikuchi et al., 2016; Fałkowski, 2010; Osborne, 2005). There is a consensus in the literature that the "buy low" and "sell high" guiding principles, at the core of the competitive storage model, are unattainable for farmers whose liquidity comes from grain sales (Stephens & Barrett, 2011; Burke et al., 2019). The reason is that farmers' decisions to sell or store grain are subject to liquidity constraints and heterogeneous price expectations. Unlike traders, smallholder farmers often also face information and physical storage constraints that limit their ability to change behavior in response to weather forecasts (Letta et al., 2021). Lastly, market participation is limited to lower value activities in developing contexts, constraining farmers' positioning to backward stages in the market value chain (African Development Bank et al., 2014).

To further complicate matters, in the presence of incomplete or missing markets (as is most often the case in developing contexts), farming households perceive food self-sufficiency as a source of protection against price risks in food markets (Fafchamps, 1992; de Janvry & Sadoulet, 2006). In this respect, food production takes on an insurance value, in addition to its regular contribution to income. The supposed benefits of agriculture commercialization on food security may be offset by transaction costs, risk aversion and low resilience capacity (Montalbano et al., 2018). On the other hand, taking the market option, prices for small producers depend on their positioning within the farmer-producing class. As such, small farmers tend to rush post-harvest production to sell their crop to the market when market price volatility goes down the value chain, pushing small producers into a vicious cycle of low productivity, low quality and low prices (Purcell, 2018).

Therefore, the empirical association between farmers' food security and market positioning is not straightforward. Most scholars have carried out quantitative assessments based on single-country studies, and context-specific frameworks mainly focused on market participation. Broader empirical assessments are hampered by difficulties in terms of both data and methodology: the market choice hinges on several factors influencing both households' decision-making process and their food security (Key et al., 2000), whereas alternative commercialization options have mixed impacts on food security (Swinnen & Vandeplas, 2014; Wohlgenant, 2001; Weldegebriel, 2004; McCorriston et al., 2001; Wang et al., 2006). As Bellemare and Bloem (2018) stress, the literature is still lacking in cross-country, multi-area and multi-year studies disentangling the endogeneity affecting contract farming decisions. Although access to competitive agricultural markets shows a positive correlation with food security (Maggio and Sitko; 2019), a thorough investigation of the specific role of key mediation factors capable of increasing the resilience of smallholder farmers is still lacking. Evidence of the welfare effects of farmers' market proximity is even scarcer.

This article seeks to fill this gap by assessing the presence of a significant association between farmers' market proximity (which we use as a proxy for market positioning), their resilience to shocks and stressors, and, in turn, their vulnerability to food insecurity. In competitive systems spatial arbitrage should lower the price differences across markets to the level of transaction costs, farmers should naturally sell at the farm gate, and shocks could hit all the market chain's nodes via standard transmission channels (Fafchamps, 1992). However, this is often not the case in developing contexts, and distance to final markets matters when determining farmers' vulnerability to market shocks. In such a scenario, farmers' resilience to shocks may be correlated with their distance from the market. Through a hybrid empirical approach - combining traditional econometric methodologies, theory-based empirical models, machine learning routines and mediation analysis - we show that farmers' market proximity is significantly and negatively associated with vulnerability to food insecurity. According to standard theory - under full certainty and efficient markets - there are no reasons to register heterogeneity in food security induced by market proximity, however we actually demonstrate that households' resilience plays a role in this. We argue that this happens because market proximity and access to markets influence households' resilience capacity in various ways: it can reduce farmers' exposure to traders' exploitation, mitigates risk exposure by allowing the sharing of information about final markets among farmers, generates positive spillovers for the actors involved and might stimulate farmers to sell higher quantities and, in turn, earn more.

These findings have relevant and actionable policy implications, as they help to prioritize interventions, not only to improve market participation but also focus on access to markets and market positioning as a crucial means to boost household resilience. They also suggest that exposure to risk is a key driver capable of reconciling the absence of welfare effects of positioning highlighted by theoretical literature with the empirical evidence of the significant welfare-enhancing effects of proximity to final markets. Our work provides three main contributions: i) unlike previous literature, we assess food security by looking at the volatility of its stochastic components rather than its mean levels (in terms of experienced food insecurity); ii) from a methodological point of view, we introduce machine learning algorithms into the estimation of a standard vulnerability model; iii) we apply an original dataset of household surveys available for eight countries from three continents, with higher external validity than previous single-country works. Note that we employ subjective measures taken from these survey data to capture both food security and resilience, in line with the increasing use in scientific literature of people's perceptions and self-reported experiences as measures of food security and resilience that can compete with, or at least complement, objective measurements, especially in data-scarce environments (Cafiero et al., 2018). Nevertheless, a sensitivity analysis replacing the subjective food security outcome with total gross income is provided to show robustness to objective measures of welfare deprivation.

The rest of the paper is arranged as follows: Sections 2 and 3 describe the relevant literature and the conceptual framework. Section 4 presents the empirical approach and identification strategies. Section 5 illustrates the data and reports some preliminary descriptive statistics. The results are presented and discussed in Section 6. Section 7 wraps up and concludes.

2. Literature review

The analysis of the costs and benefits of market channels is yet to be fully undertaken, and its many underlying assumptions lack sufficient empirical support. Accessing the market requires different choices, depending on factors like access costs and risk preferences (de Janvry & Sadoulet, 2006; Key et al., 2000; Jensen, 2010; Svensson & Yanagizawa, 2009). Also, as debated in several empirical studies on nutrition and commercialization (DeWalt, 1993; von Braun, 1995; Carletto et al., 2017), household income growth may not represent the way to food security and higher welfare levels. There are a number of reasons for this. First, cash income may be less likely to be converted in increased food intake while fostering substitution mechanisms towards non-food consumption or less nutritious foods (Bouis & Haddad, 1990; von Braun et al., 1991). Second, profits from commercialization may lead to different investment opportunities and increase the opportunity cost of current consumption, negatively impacting food costs (Abbi et al., 1991; Kennedy & Cogill, 1987; Popkin, 1980).

The literature traditionally views subsistence agriculture (i.e., crops sold to friends/neighbors or for own consumption) as the last-resort option driven by high transaction costs and missing markets or high risk-aversion (Timmer, 1997). In this respect, both fixed and proportional transaction costs significantly affect household behavior. Specifically, costs are more relevant in selling than buying choices (Key et al., 2000). Many empirical studies, such as Renkow et al. (2004), Osborne (2005), and Barret (2005), confirm the strong association between high transaction costs and subsistence agriculture by showing how traders foster households' predisposition towards subsistence agriculture in remote regions. Moreover, most farmers in developing areas view market interaction as dangerous and challenging, making them opt wholly for self-subsistence (Fackler & Goodwin, 2001; Fafchamps & Hill, 2004). Still, selling one's own crop can turn in-kind income into cash income (Kennedy & von Braun, 1995), which can be potentially used to buy goods, improving, in turn, food security (Kennedy & von Braun, 1995; Pingali, 1997; Romer, 1994; Timmer, 1997). Bellemare & Novak (2017) argue for instance that farmers involved in contract farming experience a reduction in their "hungry" season.

However, once farmers enter the market, they position differently according to their primary buyers. The latter might act through different intermediaries, trading firms or State or parastatal organizations managing assembly markets, etc. (Montalbano et al., 2018). In competitive systems, spatial arbitrage should indeed lower price differences across markets to the level of transaction costs (Fafchamps, 1992). Thus, selling at the farm gate should be the natural choice, as farmers do not have to bear the costs of bringing the produced crop to the nearest market. However, Fafchamps and Hill (2004), using original survey data for coffee producers in Uganda, found that the likelihood of selling to the market increases with both the quantity sold and proximity to the market. Mulbah et al. (2021) confirmed that high transaction costs tend to force farmers to sell at low farm-gate prices, reducing their income and increasing the risk of triggering the vicious cycle of poverty. The common wisdom is that high margins for market intermediaries tend to reduce producer margins while augmenting food prices (Coulter & Pouton, 2001). Sexton (2013) and Swinnen and Vandeplas (2014) argue that the geographic dispersion characterizing small farmers determines price margins, given the insurgence of local oligopsony imposing higher transaction costs. Physical distance to the primary market may represent a barrier to participation, and being closer to city centers may translate into being closer to the final buyer in the chain. Other scholars point to large margins for traders by considering the reduced effects of global price increases on producers (McMillan et al., 2002; Fafchamps & Hill, 2008). In this setting, participation in the market and downward positioning in the chain is associated with increased employment, better jobs, resources, governance and food security (Minten et al., 2009;

Cattaneo & Miroudot, 2013; Swinnen, 2014; Swinnen & Vandeplas, 2014).

By contrast, Montalbano et al. (2018) found that Ugandan net producers of maize able to sell their periodic surpluses in the local village, district and national markets are better off in terms of food security irrespective of decisions regarding the specific selling point. Other studies highlight the positive effects of contract schemes (Barrett et al., 2012; Bellemare, 2010; Bellemare & Novak, 2017) and the value export chain for smallholder farmers (see, inter alia, Minten et al., 2009; Subervie & Vagneron, 2013; Handschuch et al., 2013 and Asfaw et al., 2010). According to this strand, price transmission asymmetries do not vary with market power but with vertical coordination, returns to scale, degree of processing and farmers' risk behavior (Swinnen & Vandeplas, 2014; Wohlgenant, 2001; Weldegebriel, 2004; McCorriston et al., 2001; Wang et al., 2006).

For local actors, territorial sales outlets may perform better than markets, especially when their ability to recover from shocks is low. In Dar es Salaam (Tanzania) for example the raw milk system operates in a broader symbiotic local food system, and delivers more fresh milk than any other supplier. Incorporating such a system into a market chain would represent to local farmers a threat to their food security and welfare (Wegerif & Martucci, 2019). Indeed, a shock in staple food prices is more perceived by households with a food-insecure dietary regime than by those at the bottom of the caloric intake distribution pyramid (D'Souza & Jolliffe, 2014), resulting in more vulnerability to market fluctuations. A vicious circle between market participation, resilience to shock, and welfare vulnerability seems to exist, and farmers' risk aversion and resilience capacity represent critical features affecting market positioning.

3. Vulnerability, resilience and food security

Along with the increased relevance of risk analysis in development economics, scholars and practitioners are increasingly interested in developing forward-looking welfare measures. As a result, many approaches to food security, resilience and vulnerability have been proposed in recent years. However, they have advanced on parallel tracks, and less attention has been devoted to investigating the subtle links across the various notions and concepts. While a strand of the literature looks at resilience as the endogenous component of vulnerability, others underline the crucial role of the time dimension to disentangle the potential long-lasting adverse effects of shocks on welfare (Montalbano & Romano, 2023). On the other hand, the stability pillar of the most common definition of food security points to food security having a risk dimension: the food security of households certainly decreases when they cannot mitigate downside risks. Unfortunately, current literature has primarily missed this forward-looking approach apart from a few isolated cases (e.g. Haddad & Frankenberger, 2003; Løvendal & Knowles, 2006).

Our identification strategy assesses the vulnerability to food security of investigated farmers by looking at the relationship between the resilience-enhancing role of market proximity and the volatility of the stochastic components of food security. Specifically, we first test whether households closer to destination markets are less food-insecure, and then provide evidence about an existing association between market proximity and resilience. Resilience is a complex concept, comprising a multidisciplinary explanation of the interrelated dynamics of risk exposure, human living standards and ecological and social processes (Barrett et al., 2021). Although the definition of resilience is taken from other sciences, especially ecology, scholars in development economics recently started to integrate this notion in the international development sphere (Barrett et al., 2021; d'Errico et al., 2019, 2020). In development literature resilience is often defined as the capacity to ensure that shocks and stressors do not have long-lasting adverse consequences on development (Constas et al., 2014). When framed behind capacity, resilience entails a latent variable capturing the effects of a combination of observable and unobservable attributes limiting ex-ante risk exposure and the long-term consequences of shocks (Barrett et al., 2020). Hence, resilience is conceived as a set of multiple capacities. Due to data constraints, we adopt here a subjective measure of resilience, developed and collected by IFAD, based on the self-perceived capacity to recover from shocks (Garbero & Letta, 2022).

Food insecurity exists when households lack physical, social and economic access to food matching their dietary needs and preferences for a good, healthy and active life. According to Cafiero et al. (2018), households' diverse ability to achieve food security also calls into question the effectiveness of objective measurements. For such reasons, it would be preferable to consider subjective measures rather than objective ones when dealing with biased household *status quos* of food insecurity and resilience. Also, as Ibok et al. (2019) claimed, traditional measures of food insecurity vulnerability, such as food consumption or per capita intake, can be misrepresentative, as they do not account for the multidimensional aspects of food security. Under the project Voices of the Hungry, the United Nations Food and Agriculture Organization (FAO) developed a survey-based experiential measure of food security, called the Food Insecurity Experience Scale (FIES). Starting from 2014, international organizations like FAO and IFAD started including FIES in their household surveys (Cafiero et al., 2018; Wambogo et al., 2018). The FIES variable measures food insecurity based on direct experiences, and is comprised of eight questions centring on the severity of food insecurity (Smith et al., 2017; Cafiero et al., 2018). Some recent studies (Smith et al., 2017; Coates, 2013) show that FIES has turned out to be more accurate than many model-based objective measures. In the FIES raw score, respondents answer eight yes/no questions (shown in Table A.3 in the Appendix), each capturing a different aspect of food insecurity. Responses are then aggregated into an overall raw indicator of household food security, the sum of affirmative responses, 0 to 8, constituting the raw FIES score (Kansiime et al., 2021). This raw score is comparable across countries only if one checks for country-level fixed effects. According to Adjognon et al. (2021), households can fall into three categories: 1) mild food insecure, with an aggregate score of between 0 and 2; 2) moderately food insecure, with an aggregate score of between 3 and 6; and 3) severely food insecure, with aggregate scores equal to or higher than 7.

4. Empirical framework

In this empirical analysis we adopt a vulnerability measure similar to that proposed by Chaudhuri (2001 and 2003). The use of Chaudhuri's measure is motivated by its ability, in the available cross-sectional setting (see the data section), to deal with heteroscedasticity in farmers' response to market shocks, net of the individual socio-economic determinants. In this respect, vulnerability should not be considered a stand-alone concept, but needs to be framed in the household reality, where heteroscedasticity in residuals proxy different household coping strategies. For example, in Kenya and Tanzania, vulnerable small-scale farmers apply different coping strategies: a primary coping strategy that provides food and income through activities substituting farming, and a complementary coping strategy providing some food and income with auxiliary, non-self-sufficient activities (Eriksen et al., 2005).

As for the outcome variable, we follow the recent contribution by Adjognon et al. (2021), who use a *standardized* raw FIES score as their main outcome variable and standardize the raw FIES score to a scale having mean zero and standard deviation one. For sensitivity purposes, we replicate the analysis adding total gross income as an alternative outcome variable in order to derive households' welfare fluctuations. The additional use of income figures, i.e., of an objective and monetary measure of household welfare, ensures that our key results are not driven solely by the use of a subjective, non-monetary welfare measure such as self-reported food security. [1]

Inspired by the conceptual framework of household vulnerability as expected poverty (VEP) (Chaudhuri, 2001 and 2003), our empirical strategy consists of three main steps:

i. we first obtain a volatility measure by filtering our outcome variable (food security or, alternatively, income) through a machine learning-enriched Feasible Generalized Least Squares (FGLS) approach in order to obtain household-specific residuals;

[1] It is well known that income is a worse proxy for welfare than consumption, as variations in aggregate consumption are much smaller than those in aggregate income (Campbell & Deaton, 1989). We are aware of this limitation, but, unfortunately, consumption figures are not available in the IFAD dataset.

ii. we then compute our measure of vulnerability using an FGLS model;

iii. finally, we test for resilience-driven heterogeneity in the association between volatility/vulnerability and market proximity (our proxy for market positioning and access to markets) by exploiting first an instrumental variable analysis and then a mediation analysis approach based on structural equation modeling.

In step one we regress our outcome variable (standardized raw FIES score for the main analysis, total gross income for the sensitivity analysis) on a set of household characteristics, selected via a machine-learning algorithm to obtain residuals representing pure stochastic measures of food security or income volatility.[2] As standard in this setting, each household's ex ante distribution necessary to calculate its probability of food insecurity is obtained from a flexible heteroskedastic regression specification, which allows us to predict the ex ante mean and variance for each household, based on its current socio-economic characteristics (Christiaensen & Boisvert., 2000). In this setting, unexplained variance captures the impact of unobservable idiosyncratic and covariate shocks for each household, net of the available risk mitigating and coping mechanisms. The central assumption here is that variance of the error term across households mimics the inter-temporal variance by households. This assumption requires that the stationarity assumption holds up (i.e., households have the same distribution for our outcome variables). As mentioned, the primary assumption of this conceptual framework is that the unexplained variance of outcomes in our cross-sectional regression is not equal across households. In other words, here we are relaxing the assumption of homoscedasticity. As a result, to compute the robust mean and variance of our target variables, we adopt a three-step FGLS model. To this end, we first use machine learning algorithms to select among all possible combinations of household characteristics only the most predictive ones, to obtain pure stochastic residuals, as follows:

$$y_{ht} = X_h\beta + e_{ht} \qquad [1]$$

where y_{ht} represents the outcome variable, standardized raw FIES score or, alternatively, total gross income, proxying out the latent welfare variable, X_h is a bundle of observed household characteristics, β a vector of parameters, and e_{ht} the stochastic components. The ability to filter out these pure stochastic components from the deterministic part of our target variables is key in this kind of exercise. To this end, we exploit the predictive power of Least Absolute Shrinkage and Selection

[2] We are aware that as the raw FIES score is a discrete outcome variable, an ordered probit model could be employed to estimate the simple conditional probability of being food insecure. However, since we are interested in computing more complex measures of volatility and vulnerability to food insecurity, we apply the well-established FGLS procedure developed by Chaudhuri (2001, 2003) and, following the recent paper by Adjognon (2021), use the raw FIES score as the outcome variable in multivariate linear regression models. In any case, note that our results are robust to the use of a continuous outcome variable, namely total gross income.

Operator (LASSO), a supervised machine learning routine based on regularized regression (Hastie et al., 2009). LASSO makes it possible to select the most predictive control variables from a more extensive set of features. As residual filtering is ultimately the outcome of a predictive task, the comparative advantage in predictive power that machine learning routines hold over traditional regression approaches can lead to a more accurate prediction of the outcome and related residuals in this first FGLS step. [3] After applying LASSO, in order to make the standardized raw FIES scores comparable across countries, we regress the obtained residuals on country dummies.

In the second step of the FGLS procedure, the filtered residuals from the first stage [1] are used to obtain an estimate of the variance:

$$\hat{e}^2{}_{ols,h} = X_h \theta + \eta_h \qquad [2]$$

It is worth noting here that X_h now includes only the combination of household characteristics not dropped by the LASSO procedure in step [1].

The predictions from [2] lead to a robust OLS estimate of the FGLSβ coefficient simply by calculating:

$$\frac{y_{ht}}{\hat{\sigma}_{e,h}} = \left(\frac{X_h}{\hat{\sigma}_{e,h}}\right) \beta + \left(\frac{e_h}{\hat{\sigma}_{e,h}}\right) \qquad [3]$$

where $\hat{\sigma}_{e,h}$, which is equal to $\sqrt{X_h \hat{\theta}_{FGLS}}$, is a consistent estimate of the volatility of our household outcome variable. We then construct a volatility dummy considering as "volatile" only households lying above the median of the obtained volatility distribution.

Finally, we can estimate the forward-looking vulnerability measure, i.e., the probability that a household h with X characteristics will be food insecure (or poor, in the case of income) in the near future, using the predicted standardized raw FIES scores through a proxy of the intertemporal distribution of standardized raw FIES scores, whose mean and variance are computed as follows:

$$\hat{E}[\ y_h \,|X_h] = X_h \hat{\beta}_{FGLS} \qquad [4]$$

and

$$\hat{V}[y_h|X_h] = \hat{\sigma}_{e,h} = \sqrt{X_h \hat{\theta}_{FGLS}} \qquad [5]$$

Hence, our final adjusted vulnerability measure will be equal to:

[3] In addition to the set of control variables, we also include all the pairwise interactions among them as additional predictors to capture potential nonlinearities and important interactions among features.

$$\hat{V}_h = \Pr[y_h > z \mid X_h] = \phi\left(\frac{X_h\hat{\beta} - z}{\sqrt{X_h\hat{\theta}}}\right) \quad [6]$$

where z represents the food insecurity (poverty, for income) line and $\phi(.)$ the cumulative density of the standard normal. In order to test the robustness of our results, we derive the FIES vulnerability measure V_h considering two alternative food insecurity lines: one equal to the standardized raw FIES score median and another equal to Adjognon et al. (2021) mild food insecurity line threshold of the raw FIES score equal to 3. Note that, for our two alternative outcomes, food insecurity and income, the construction and interpretation of the threshold line are reversed: food-insecure households are those who move *above* the food insecurity line, whereas in the case of income households fall into deprivation if they move *below* the poverty line.

Once we obtain $\hat{V}_h$, i.e., an estimated measure of the probability of moving above (below) the food insecurity line (the poverty line) in the near future, we then construct a vulnerability dummy which, in the case of food insecurity, is equal to 1 when this probability $\hat{V}_h$ is above 50% for the first food insecurity line and equal to 25% for the alternative line [4] and, in the case of income, is equal to the median of the income distribution.

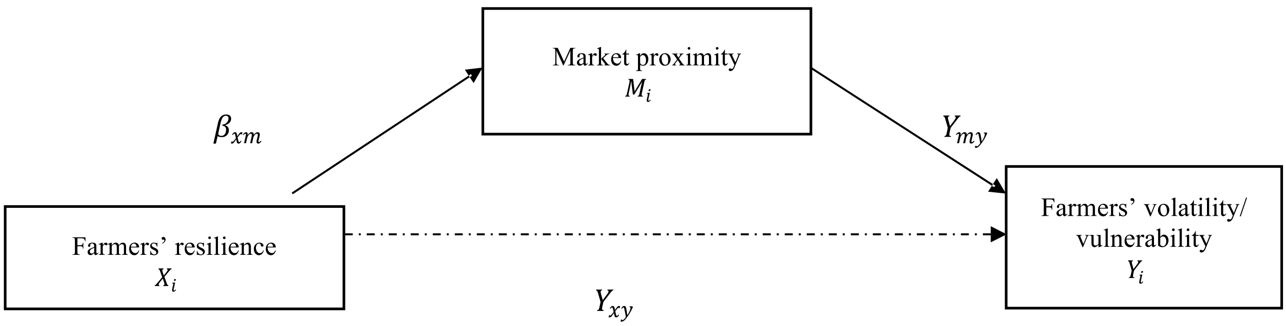
After building these measures of interest, we are finally able to investigate the association between market proximity, resilience and volatility/vulnerability. As stated above, the resilience variable we employ (the ability to recover) is an overall subjective metric of the ability to recover from various shocks and stressors. Under the hypothesis of complete and efficient markets, proximity to final markets should be uncorrelated with welfare fluctuations and vulnerability. In this setting, market proximity can be used as an instrument or restriction capable of influencing food security only via resilience. Therefore, to address the endogeneity of resilience with respect to the outcome measures, we implement an instrumental variable approach in which market proximity is used as the instrument for household resilience. We thus assume that it is uncorrelated with the error term but strongly related to resilience, and our exclusion restriction states that market proximity does not affect food security fluctuations other than through its impact on resilience capacity. We do not have explicit measures of market positioning (the first-best variable for our purposes) in the IFAD dataset: the considered dataset does not provide uniform and comparable information on the harvested crops' primary seller(s). Therefore, we adopt a workable solution: we proxy market positioning by proximity to markets, which is calculated as each farmer's distance from the nearest urban center, following extensive literature using distances from cities or major population centers as measures of market

[4] We use two different threshold cutoffs for the V_h distribution, since higher levels of raw FIES score imply an increased skewness in the V_h distribution and, in turn, a lower share of vulnerable households as one moves along the distribution.

access and participation (Amarasinghe et al., 2005; Azzarri & Signorelli, 2020; Muto & Yamano, 2009; Xu et al., 2009). [5] We are aware that proximity to markets may not be exogenous in absolute terms in respect of food security *levels* (where farmers live may be potentially correlated with many socioeconomic characteristics, country-specific factors, etc.), but we argue that it is plausibly exogenous in respect of the *fluctuations* of food security *after* filtering the confounding role of those characteristics in the preceding steps.

After testing this simple instrumental variable model, we delve further into the investigation of detected associations to better understand the transmission mechanisms. A way to see how the impact of resilience on farmers' welfare fluctuations and vulnerability is mediated by market proximity is to apply a mediation analysis via Structural Equation Modeling (SEM). SEM is a multivariate technique implementing a system of linked regression-based equations to fathom the complex relationship behind a set of observed and unobserved variables (Gunzler et al., 2013) whose foundation has solid structuring in the literature (e.g., *inter alia*, Baron & Kenny, 1986; Imai et al., 2010; Hicks & Tingley, 2011).[6] As Gunzler et al. (2019) argue, one of the main advantages of applying such a mediation model is that its conceptual nexus can be easily understood via a simple visual representation, as follows:

Figure 1: The conceptual nexus



Source: Authors' elaboration.

In our case, market proximity - proxied by the inverse of the distance from the nearest urban center - represents the mediator variable, whereas farmer resilience is the intermediate outcome, and farmers' volatility/vulnerability the final outcome. Our SEM approach is then operationalized in the following system of equations:

[5] Note that since most of the IFAD data mainly focus on farmers, we are primarily focusing on a specific segment of the value chain, with no information on other upstream segments (i.e., buyers, intermediaries, etc.).

[6] Baron and Kenny (1986) developed an SEM approach estimating causal mediation effects by decomposing the total treatment effect into indirect and direct effects. The indirect effect resulted in explaining how the treatment works through the considered mediator, and the direct effect represents all the other factors affecting the dependent variable.

$$M_i = \beta_0 + \beta_{xm} X_i + \epsilon_{mi} \quad [7]$$

$$y_i = y_0 + y_{my} z_i + y_{xy} x_i + \epsilon_{yi} \quad [8]$$

where y_{xy} represents the direct effect of resilience on volatility/vulnerability and $\beta_{xm} * y_{my}$ the indirect effect on volatility/vulnerability via market proximity. The additional use of income figures, i.e., of an objective and monetary measure of household welfare, ensures that our key results are not driven by the use of a subjective, non-monetary welfare measure such as self-reported food security.

5. Data and descriptive statistics

Our database is formed by a pool of cross-sectional farmer households' data from a set of standardized surveys carried out by IFAD for its impact evaluations and assessments (the 'IFAD10' database). There are currently only two studies exploiting this novel data source to investigate, respectively, whether agricultural interventions can improve food security and nutrition (Garbero & Jäckering, 2021), and whether machine learning routines can predict household resilience for policy targeting purposes (Garbero & Letta, 2022). The subsample of the original IFAD10 database that we use, which contains data for all the key variables we need, including a proxy for household resilience, incorporates a total of more than 15,000 initial observations across eight countries (Bangladesh, Brazil, Chad, Indonesia, Mexico, Nepal, Sao Tomé & Principe, and Senegal) collected between 2017 and 2018 (see Figure 2 below).

Figure 2: Map of countries in the considered sample

Source: Authors' elaboration.

Descriptive statistics for a set of common basic demographic and socio-economic characteristics of households in our sample are reported in Tables A.1. and A.2. in the Appendix. Household heads in the sample are on average 48 years old, have four years of schooling, and are generally male. On average, each household comprises six people, generally four adults and two children in terms of composition. Aside from the head, average household members have more than four years of schooling and have barely attained the first level of education. In terms of ownership, each household in the sample owns on average 5 ha of land and very few other assets (both the Asset index and the Agricultural asset index are below 15%). Households in the sample are generally poor, with a total gross income averaging below 3 thousand dollars.

Weiss et al. (2018)'s *Global Accessibility Map* was integrated with the IFAD10 database to derive the distance from the nearest urban center. The map quantifies travel time to cities in the year 2015, just before our survey data were collected at a spatial resolution of approximately one by one kilometer by integrating 10 global-scale surfaces characterizing factors affecting human movement rates and 13,840 high-density urban centers within an established geospatial-modeling framework (Weiss et al., 2018). [7] Descriptive statistics, country by country, for the average distance from the nearest urban center, our proxy for market proximity, are shown below.

On average, the households under review are 43 km away from the primary market, positioning in the first quarter of the maximum observed distance range. Specifically, households in Brazil are furthest away from the main market, while those in Senegal and Mexico are the nearest. On the other hand, data from countries like Chad and Mexico show very high standard deviation values, and put households 54-58 km away from the primary market on average. Lastly, distance measures are not available for all observations due to missing coordinates for a subsample of households. These missing values were dropped from our analysis.

Table 1: Distance from the nearest urban center (km) – Descriptive statistics

Variable name	N. of observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Bangladesh	1,968	46.41	17.72	11.80	81.90
Brazil	1,386	63.11	17.66	3.70	106.70
Chad	1,555	57.76	44.17	4.40	181.20
Indonesia	1,553	26.96	21.24	1	78.70
Mexico	1,631	54.29	23.89	4.50	108.30
Nepal	2,864	44.51	22.35	1.20	84.70
Sao Tomé & Principe	1,153	10.12	4.72	0.40	27.50
Senegal	2,177	35.51	23.21	1.70	107.90
Average	14,287	43.08	28.05	0.40	181.20

[7] An urban center is defined by Weiss et al. (2018) as a contiguous area with 1,500 or more inhabitants per square kilometer or a majority of built-up land cover coincident with a population center of at least 50,000 inhabitants.

Table 2 below gives summary statistics for the household-level raw FIES score. In our sample, the share of households that show some degree of food insecurity (i.e., households replying positively to at least one of the questions in the questionnaire) is, on average, close to 65% of the total interviewed. Households with severe food insecurity levels (raw FIES score equal or above 7) make up over 10% of the total, and those with moderate food insecurity levels (raw FIES score equal or above 3) make up 41% of the total sample size. As in the case of market proximity, Chad is among the countries performing worst in the sample, with 493 households of the 2,174 interviewed with a raw FIES score equal to 8.

Table 2: Raw FIES score – Descriptive statistics

Variable name	N. of observations	Mean	Standard Deviation
Bangladesh	1,970	2.32	2.39
Brazil	1,386	2.11	2.40
Chad	2,174	3.74	3.03
Indonesia	2,028	1.50	2.15
Mexico	1,760	1.91	1.94
Nepal	2,874	1.12	1.51
Sao Tomé & Principe	1,269	4.17	2.71
Senegal	2,181	3.10	2.41
Average	15,642	2.39	2.52

Finally, we report descriptive statistics of our variable capturing household resilience, the Ability to Recover (ATR) indicator. The ATR metric is constructed based on answers to the question: "To what extent were you and your household able to recover from shock *x*?". ATR is a self-assessment from the interviewed household taking the form of an ordinal variable on a scale ranging from 1 to 5:

a. Did not recover (=1);
b. Recovered to some extent, but worse off than before (=2);
c. Recovered to the same level as before (=3);
d. Recovered, and better off than before (=4);
e. Experienced the shock but was not significantly affected (=5)

The question is repeatedly asked for a roster of several different *x* shocks (droughts, floods, crop diseases, etc.) potentially experienced in the years before the survey. We follow Garbero and Letta (2022) and compute household-level ATR as an average of all the values of the various abilities to recover reported by the household for each shock of the survey module. As shown in Table 3, the investigated households tend to not be resilient to shocks, as they report, on average, an inability to recover to their previous level of welfare after the occurrence of a variety of shocks and stressors.

Table 3: Ability to Recover (ATR) – Descriptive statistics

Variable name	N. of observations	Mean	Standard Deviation
Bangladesh	1,177	2.34	0.89
Brazil	1,345	2.26	1.22
Chad	1,981	1.62	0.90
Indonesia	1,104	3.69	1.02
Mexico	1,159	2.26	1.00
Nepal	1,304	2.61	1.23
Sao Tomé & Principe	567	2.39	1.26
Senegal	1,498	3.22	1.24
Average	10,135	2.49	1.26

Among the countries studied, only household samples from Senegal and Indonesia show an average value of resilience above the resilience threshold of 3, signaling the ability to return to the same level of welfare as before the shocks. Still, on average, households can recover from shocks only to some extent, and are worse off, in terms of welfare, compared to the pre-shock situation. Observations for ATR are incomplete, and reduce our sample of analysis to around 10,000 units.

6. Results

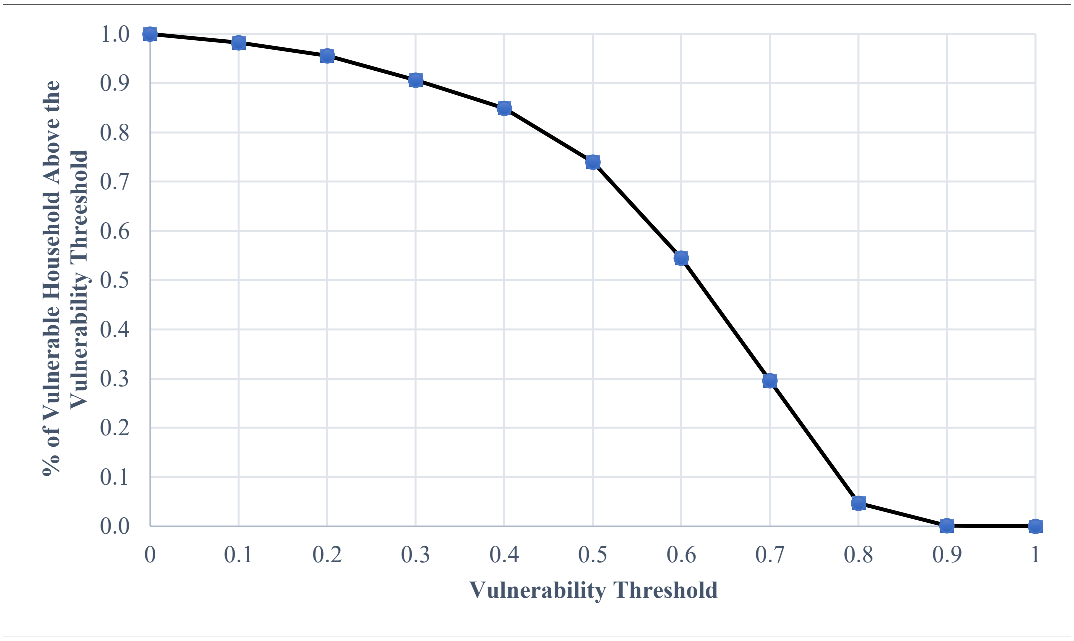
We start by presenting the results for the main outcome variable, food insecurity. The discussion of income results is relegated to subsection 6.2, and the overall discussion of the results to subsection 6.3.

6.1 Main results on food insecurity

The results from the LASSO filtering procedure (Equation 1) are reported in Table A.4 in the Appendix. The estimated LASSO residuals are then regressed on country dummies. In the second step (Equation 2), we regress the estimated residuals on the combinations of household characteristics previously selected by LASSO. As shown in Figure A.1 in the Appendix, the resulting filtered residuals, capturing volatility to food insecurity, follow an approximately normal distribution, confirming the appropriateness of the filtering methodology.

After constructing the volatility dummy (considering as "volatile" only those households situated above the volatility median), we then apply the vulnerability procedure (Equations 4 and 6 in Section 4) and obtain through Equation 6 the adjusted vulnerability estimate, representing the household probability of being above the food insecurity line, equal to the median value of the standardized raw FIES score (in our case, equal to raw FIES score 2). The FIES vulnerability estimate $\hat{V}_h$ is represented in Figure 3 below. As displayed in Figure 3, no household in the sample has a 100% probability of being vulnerable in the future, although half of them are more than 60% likely to be vulnerable in the near future.

Figure 3 – The adjusted FIES vulnerability estimate



We then construct a vulnerability dummy based on the $\hat{V}_h$ estimate obtained above. Starting from the adopted food insecurity line, we consider "vulnerable" only households with a probability of falling into food insecurity in the near future greater than 50% (i.e., more likely than not to be vulnerable). Hence, our vulnerability dummy is sensitive to both the adopted probability threshold and food insecurity line. We also provide some robustness checks here. First, for the sake of consistency with the current literature (Adjognon et al., 2021), we also set the food insecurity line equal to 3 (raw score), marking the first level of moderate food insecurity. Second, we also test the probability threshold at 25% instead of 50% to enlarge the population target.

We finally investigate the role of resilience (proxied by ATR) in mitigating volatility and vulnerability through proximity to markets. The instrumented variable is the ATR resilience variable. The instrument is our proxy for proximity and access to markets, i.e., the inverse distance (in km) from the nearest urban center. Table 4 shows the estimated coefficients for the instrumental variable (IV) model described in Section 4, for three different outcomes : i) when the dependent variable is the estimated dummy volatility; ii) when the dependent variable is the vulnerability dummy resulting from the food insecurity line equal to the median of the standardized raw FIES score and vulnerability threshold 0.5 and, iii) when the dependent variable is the vulnerability dummy resulting from the food insecurity line equal to raw FIES score three and vulnerability threshold 0.25. [8] All estimates present

[8] In all cases, the F-test statistics from the first stage abundantly exceed the rule-of-thumb value of 10.

consistent results, showing that a negative and statistically significant association exists between resilience (instrumented with market proximity) and food insecurity fluctuations.

Table 4: FIES Instrumental variable model

Dependent variable:	Food insecurity volatility	Food insecurity vulnerability (FI line = median, *vx* >= 0.50)	Food insecurity vulnerability (FI line = FIES value 3, *vx* >= 0.25)
ATR	-0.194***	-0.157***	-0.212***
	(0.0258)	(0.0280)	(0.0289)
Observations	9,126	9,126	9,126
Wald Chi-Squared	56.66	31.42	53.53
Prob>Chi-Squared	0.0000	0.0000	0.0000

*Notes: t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The excluded instrument is the inverse of the distance from the nearest urban center. The FIES volatility dummy takes value one if FIES volatility is above the distribution's median and 0 otherwise. In the case of the food insecurity line equal to the median (FIES=2), the FIES vulnerability dummy takes value one if FIES vulnerability (vx) is above the distribution's median and 0 otherwise. In the case of the food insecurity line equal to FIES value 3, the FIES vulnerability dummy takes value one if FIES vulnerability (vx) is above the 25th percentile of the distribution and 0 otherwise. Robust standard errors in parentheses. Intercepts not reported.*

We then proceed to validate our hypothesis that a significant share of the mitigating impact of ATR on FIES fluctuations comes through the resilience-enhancing role of market proximity, as proxied by the inverse of the distance (in km) from the nearest urban center. To this end, we apply the SEM-mediation analysis model of Equations 7 and 8 in Section 4. Table 5 reports the mediation analysis results applied to food security volatility. The model suggests that market proximity is mediated by almost 6% (-0.00323/-0.0556) of the total dampening effect of resilience on FIES volatility. We replicate the same procedure for the FIES vulnerability measures and report the results in Columns 2 and 3 of Table 5. In this case, the share of the mediated indirect effect is more than 11% (-0.00305/-0.0267) for FIES vulnerability with the food insecurity line equal to the median of the standardized raw FIES score and vulnerability threshold equal to 0.50 and almost 9% (-0.00393/-0.0438) for FIES vulnerability with the food insecurity line equal to raw FIES score three and vulnerability threshold equal to 0.25. In short, being closer to the final market boosts household resilience and accounts for a significant share of the neutralizing role played by resilience in mitigating food security fluctuations and vulnerability to food insecurity.

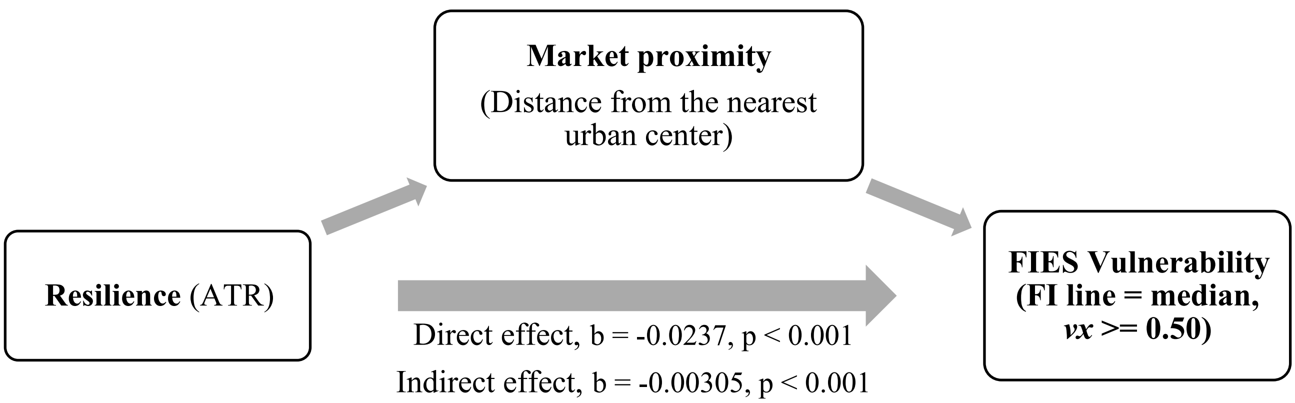
Table 5: FIES Structural Equation Model

	[1]	[2]	[3]
Dependent variable:	**Food security volatility**	**Food security vulnerability (FI line = median, *vx* >= 0.50)**	**Food security vulnerability (FI line = FIES value 3, *vx* >= 0.25)**
Total effect	-0.0556***	-0.0267***	-0.0438***
	(-13.73)	(0.00318)	(0.00376)
Direct effect	-0.0523***	-0.0237***	-0.0399***
	(-12.91)	(0.00309)	(0.00378)
Mediated (or indirect) effect	-0.00323***	-0.00305***	-0.00393***
	(-5.00)	(0.000673)	(0.000679)
Observations	9,126	9,126	9,126
Mediation effect as a percentage of the total effect (%)	5.80%	11.42%	8.97%

Notes: t statistics in parentheses. * *$p < 0.05$,* ** *$p < 0.01$,* *** *$p < 0.001$. The excluded instrument is the inverse of the distance from the nearest urban center. Bootstrapped standard errors in parentheses. The FIES volatility dummy takes value one if FIES volatility is above the distribution's median and 0 otherwise. In the case of the food insecurity line equal to the median (FIES=2), the FIES vulnerability dummy takes value one if FIES vulnerability (vx) is above the distribution's median and 0 otherwise. In the case of the food insecurity line equal to FIES value 3, the FIES vulnerability dummy takes value one if FIES vulnerability (vx) is above the 25th percentile of the distribution and 0 otherwise.*

Figure 4 shows the key results of our mediation analysis, picturing the critical mediating role of market proximity in the relationship between resilience and FIES vulnerability.

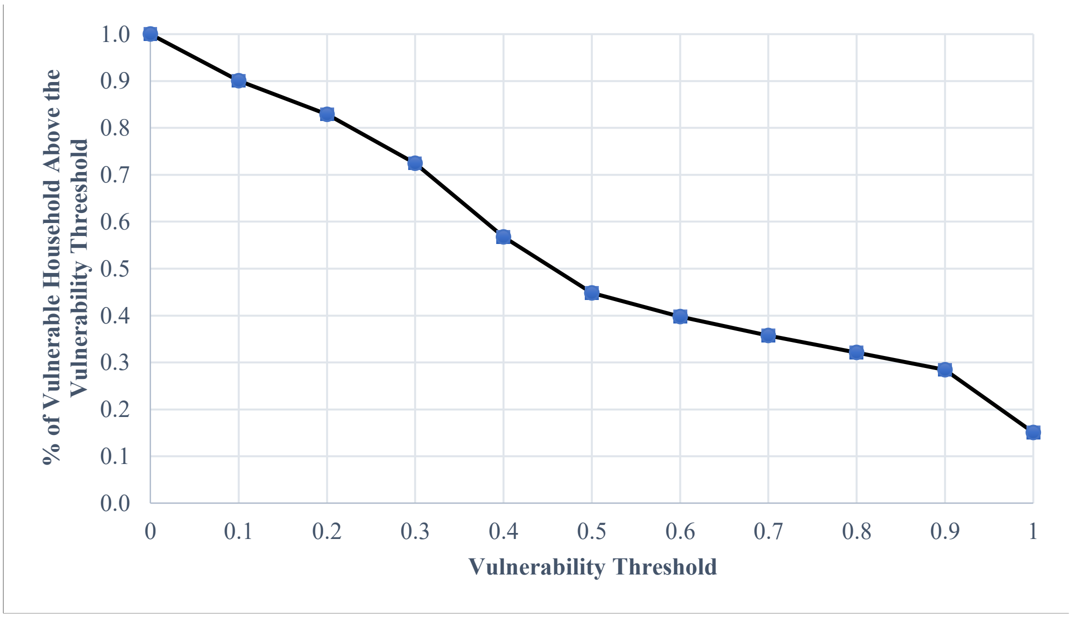
Figure 4: FIES Structural equation model



6.2 Sensitivity analysis using income

Table A.5 in the Appendix shows the outcomes of the LASSO filtering methodology for income. Just as for FIES, the resulting volatility distribution using the LASSO selected variables is a good approximation of the normal distribution (see Figure A.2 in the Appendix). We then reproduce the FGLS and the vulnerability procedure applied for FIES, with a poverty line threshold equal to the median value of the considered income distribution. The adjusted vulnerability estimates $\hat{V}_h$ for income are shown in Figure 5.

Figure 5 – The adjusted income vulnerability estimate



In the same way as for FIES, we construct a volatility dummy for income considering as "volatile" only those households situated above the median of the income volatility distribution and a vulnerability dummy considering as "vulnerable" only households with a probability of being vulnerable $\hat{V}_h$ greater than 50%. We then replicate the IV and SEM models of FIES for income. Like in the case of FIES, resilience instrumented through market proximity is negatively related to both income volatility and vulnerability (see Table 6). [9] Overall, the results of the IV models on income align with the FIES ones.

[9] As in the case of FIES, F-test statistics from the first stage strongly reject the hypothesis of a weak instrument.

Table 6: Income instrumental variable model

Dependent variable:	Income volatility	Income vulnerability (PL line = median, *vx* >= 0.50)
ATR	-0.186***	-0.338***
	(0.0253)	(0.0294)
Observations	9,233	9,233
Wald Chi-Squared	56.19	132.27
Prob>Chi-Squared	0.0000	0.0000

Notes: t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *The excluded instrument is the inverse of the distance from the nearest urban center. The income dummy takes value one if income volatility is above the distribution's median and 0 otherwise. The income vulnerability dummy takes value one if income vulnerability (vx) is above the distribution's median and 0 otherwise. Robust standard errors in parentheses. Intercepts are not reported.*

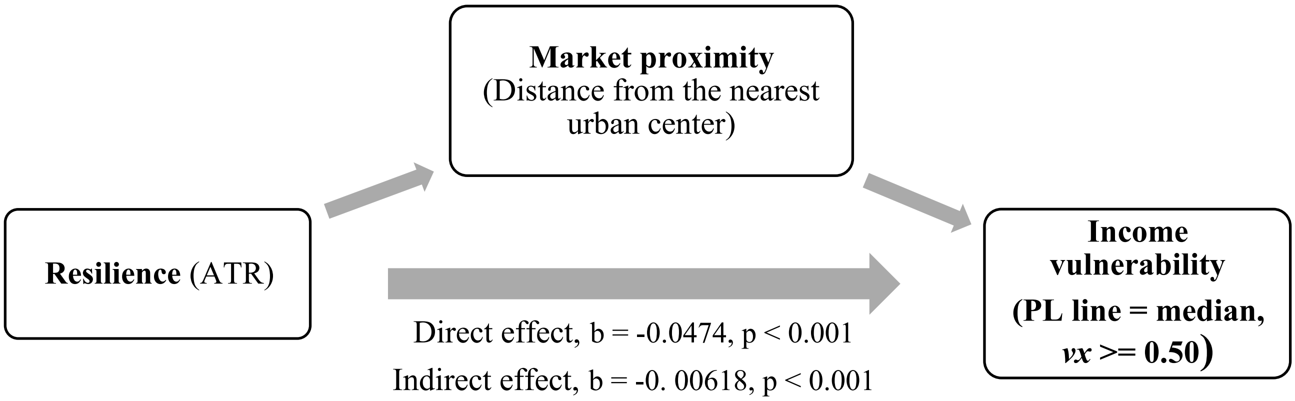
With regard to the mediation analysis, Table 7 reports the results of the SEM for income. In a very similar way to FIES, proximity to markets accounts for approximately 4% of the total dampening effect of resilience on income volatility and 11.55% of the total dampening effect of resilience on household vulnerability to welfare fluctuations. The estimated effects are statistically significant at the 1% level. Figure 6 summarizes the outcomes of the SEM model for income vulnerability.

Table 7: Income structural equation model

Dependent variable:	[1] Income volatility	[2] Income vulnerability (PL line = median, *vx* >= 0.50)
Total effect	-0.0615***	-0.0535***
	(-15.54)	(0.00351)
Direct effect	-0.0588***	-0.0474***
	(-14.86)	(0.00350)
Mediated (or indirect) effect	-0.00271***	-0.00618***
	(-4.65)	(0.000829)
Observations	9,233	9,233
Mediation effect as a percentage of the total effect (%)	4.40%	11.55%

Notes: t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *The excluded instrument is the inverse of the distance from the nearest urban center. Bootstrapped standard errors in parentheses. The income volatility dummy takes value one if income volatility is above the distribution's median and 0 otherwise. The income vulnerability dummy takes value one if income vulnerability (vx) is above the distribution's median and 0 otherwise.*

Figure 6: Income structural equation model



Therefore, like in the case of FIES and in line with the outlined IV models, the indirect effect of resilience (i.e., ATR) via market proximity on income volatility and vulnerability is always negative.

6.3 Discussion

Overall, these results are new in the literature on household food security and welfare. Resilience proxied by market proximity significantly influences vulnerability. As such, proximity to market hubs implies lower vulnerability. Hence, downward positioning in the market chain, i.e., being closer to the market, reduces FIES and income fluctuations. Previous studies (Pace et al., 2022, Slimane et al., 2013) reached a consensus on different factors influencing food security. Their evaluated mediator intensity was hardly above 15% of the total effect. In line with these studies, according to our main estimates, the indirect effect of resilience (through closeness to markets) on food security, as well as income, vulnerability is above 11% of the total explained total effect, with the food security/poverty line set at the median value of the standardized raw FIES score (equal to the raw FIES score 2). The sensitivity analysis conducted on income confirmed our results. Table 8 summarizes the results of the mediation analysis for all the various specifications and outcome variables.

Table 8: Summary table for the mediation analysis

	Point estimate	Share of the total effect
Indirect effect of ATR (via inverse distance from the market) on:		
Food insecurity volatility	-0.00323***	5.80%
Food insecurity vulnerability (FI line = median, *vx*>=0.50)	-0.00305***	11.42%
Food insecurity vulnerability (FI line = FIES value 3, *vx*>=0.25)	-0.00393***	8.97%
Income volatility	-0.00271***	4.40%
Income vulnerability	-0.00618***	11.55%

7. Conclusions

Crop commercialization is one of the main drivers of modern-day economic development. Although the study of farmers' market decisions dates back to the 1990s (Fafchamps, 1992; von Braun, 1995; Key et al., 2000), a systematic approach to relations between market proximity, resilience and vulnerability to food insecurity is still missing. In this work, we tested whether market proximity is associated, via increased resilience, with a reduction in farmers' food insecurity levels, welfare fluctuations and vulnerability. To this end, we used an original microdata set elaborated by IFAD for their cross-country impact assessments. Is being closer to the market significantly associated with higher resilience to shocks and food security? Our preliminary correlation estimates suggest that the answer is yes. Specifically, the outcomes of our empirical exercise reveal that downward positioning in the market chain increases resilience and this, in turn, reduces volatility and vulnerability to food insecurity and poverty. Due to the limitations of our estimates, this should not be interpreted in a causal manner. However, our mediation analysis shows that standard theory misses an important part of the story, that is the role of market proximity in increasing households' resilience. Although, due to data constraints in our cross-country database, we cannot explicitly test for the transmission channels and specific mediating factors at play, we argue that this likely happens because market proximity and access to markets can affect households' resilience capacity in various ways: among many potential channels, it can reduce farmers' exposure to traders' exploitation, limit risk exposure by allowing the sharing of information about final markets among farmers, generate positive spillovers for the actors involved and stimulate farmers to sell higher quantities and, in turn, earn more. The explicit identification and testing of these microchannels is deferred to future research.

Overall, these findings should encourage policymakers to prioritize agricultural-specific policies to target food insecurity hotspots (Garbero & Jäckering, 2021) and interventions such as better transport infrastructure, lower transaction costs and accessible new technologies to improve market proximity as crucial ways of boosting household resilience in rural developing contexts (see, *inter alia*, Renkow et al., 2004 and Mulbah et al., 2021). Looking forward to future research, it will be essential to identify the risk channels that determine the fragility of local markets, enabling us to reconcile the absence of the welfare effects of positioning highlighted by theoretical literature with the empirical evidence of the welfare-enhancing effects of being closer to final markets. Household vulnerability to external shocks may indeed arise in the presence of markets (Bellemare et al., 2013) if this is not counterbalanced by higher resilience capacity. In this framework, policy making must consider improving road and connectivity infrastructure and boosting farmers' market positioning and access to markets as a key means to foster resilience and inhibit food security volatility and vulnerability.

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Appendix

Table A.1. Variable definitions and other basic information

Variable name	Definition	Time period	Source
Age of the household head	Age of the household head *(decimals)*	2017 – 2018	International Fund for Agricultural Development
Education years of the household head	Years of schooling of the household head *(decimals)*	2017 – 2018	International Fund for Agricultural Development
Gender of the household head	Gender of the household head *(binary, 1=female)*	2017 – 2018	International Fund for Agricultural Development
Household size	Number of people in the household *(decimals)*	2017 – 2018	International Fund for Agricultural Development
Household average education level	Average education level attained by the household members *(values from 0 to 3)*	2017 – 2018	International Fund for Agricultural Development
Land area	Area of land owned by the household *(ha)*	2017 – 2018	International Fund for Agricultural Development
Total gross income	Household total gross income from all sources *(USD)*	2017 – 2018	International Fund for Agricultural Development
Asset index	Asset index based on common durable assets *(values from 0 to 1)*	2017 – 2018	International Fund for Agricultural Development
Agricultural asset index	Agricultural assets index based on common durable assets *(values from 0 to 1)*	2017 – 2018	International Fund for Agricultural Development

Table A.2. Summary statistics – Whole sample

Variable name	N. of observations	Mean	Standard Deviation	Minimum Value	Maximum Value
Age of the household head	15642	47.71	13.80	12	110
Education years of the household head	15642	4.11	4.20	0	28
Gender of the household head	15642	0.17	0.37	0	1
Household size	15642	5.76	3.83	1	30
Household average education level	15642	0.94	0.85	0	3
Land area	15642	5.33	10.25	0	281
Total gross income	15894	2732.39	6943.331	0	97497
Asset index	15642	0.13	0.14	0	1
Agricultural asset index	15642	0.14	0.18	0	1
Treated	15642	0.48	0.50	0	1

'Gender of the household head' is a dummy taking value 1 if the household head is female and 0 otherwise. 'Household education level' is a categorical variable which can take the following values: 0=no education; 1=primary education; 2=secondary education; 3=higher education. 'Total gross income' is calculated as the sum of total cash and in-kind wage from agricultural employment; total cash and in-kind wage from all non-agricultural employment; sales of crop and other products, together with own consumption; sales of livestock, carcasses, and other products, together with own consumption; total sales and earnings from self-employment activities; private funds (remittances, transfers from individuals) and public funds (pensions, social transfers); and other sources of income like a land rental. 'Asset Index' and 'Agricultural Asset Index' are standardized measures of assets which range from 0 to 1 and have been generated for each country sample via factor analysis, using exclusively the assets that were common across all the datasets. 'Treated' is a dummy taking value 1 if the household was in the treatment group and 0 otherwise.

Table A.3: The FIES questionnaire and raw score descriptive statistics

During the last 12 MONTHS, was there a time when a lack of money or other resources? (Q1) You were worried you would not have enough food to eat (WORRIED) (Q2) You were unable to eat healthy and nutritious food (HEALTHY) (Q3) You ate only a few kinds of foods (FEW FOODS) (Q4) You had to skip a meal (SKIPPED) (Q5) You ate less than you thought you should (ATE LESS) (Q6) You ran out of food (RAN OUT) (Q7) You were hungry but did not eat (HUNGRY) (Q8) You went without eating for a whole day (WHOLE DAY)

	Number of observations by raw FIES score								
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Bangladesh	737	157	198	358	138	110	109	108	55
Brazil	602	114	130	153	144	107	37	32	67
Chad	445	248	235	264	126	128	110	125	493
Indonesia	1,073	259	180	187	112	56	42	68	51
Mexico	541	371	302	204	126	83	76	57	0
Nepal	1,531	285	559	369	62	19	7	5	37
Sao Tomè & Principe	235	80	61	99	106	176	177	248	87
Senegal	473	165	258	433	261	174	182	108	127
Total	5,637	1,679	1,923	2,067	1,075	853	740	751	917

Table A.4: FIES LASSO filtering methodology

Dependent variable:	**Standardized raw FIES score**
Age of the household head	-0.00185
Education years of the household head	-0.0349
Household size	0.0152
Land area	-0.00404
Education years of the household head^2	-0.000256
Gender of the household head *(1=female)Land area**	-0.00252
Age of the household head*Asset index	-0.00298
Age of the household head*Treated	-0.0000811
Education years of the household head*Treated	-0.00410
Asset index*Agricultural asset index	-0.972
Asset index*Treated	0.0406
Asset index^2	-0.427
Agricultural asset index^2	-0.284
Constant	0.249
Observations	15,865

*Notes: The variables whose coefficients were set to zero by the LASSO model are dropped. Only retained coefficients are shown. Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimates signal correlation and not causality.*

Table A.5: Income LASSO filtering methodology

Dependent variable:	**Total gross income**
Age of the household head	0.0131
Education years of the household head	0.133
Gender of the household head ***(1=female)***	-0.376
Household education level	0.0332
Age of the household head*Household size	0.000528
Age of the household head* Household education level	0.00192
Age of the household head*Land area	0.000200
Household size*Land area	0.000197
Gender of the household head ***(1=female)*** ***Land area**	0.00183
Age of the household head* Agricultural asset index	0.00200
Age of the household head*Treated	0.00221
Education years of the household head*Treated	0.0303
Household size*Treated	0.00652
Household education level*Asset index	0.0620
Asset index*Treated	-1.372
Asset index^2	2.203
Agricultural asset index^2	3.435
Constant	4.243
Observations	16,119

Notes: The variables whose coefficients were set to zero by theLASSO model are dropped. Only retained coefficients are shown. Robust standard errors in parentheses. * *$p < 0.05$,* ** *$p < 0.01$,* *** *$p < 0.001$. Estimates signal correlation and not causality.*

Figure A.1 – FIES FGLS-Generated Variance

Standardized raw FIES Score with LASSO Controls

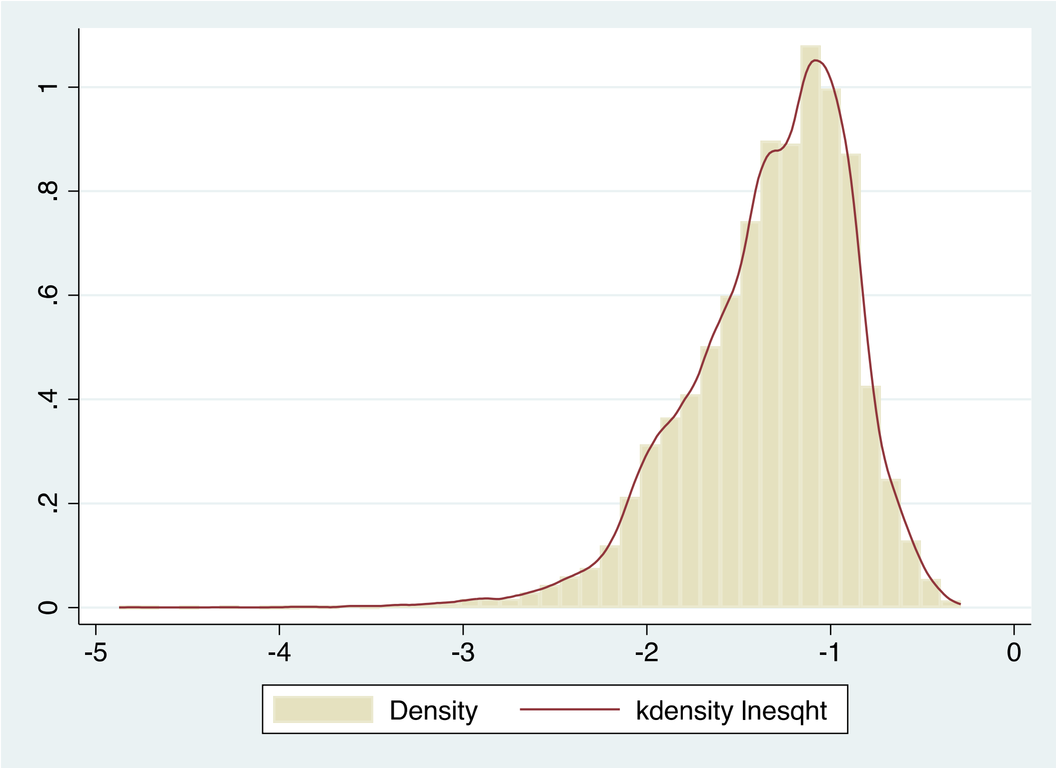

Figure A.2 – Income FGLS-Generated Variance

Natural Log Income with LASSO Controls